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Technological Learning In Energy Optimisation Models And Deployment Of Emerging Technologies

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Presented by:
Leonardo Barreto
BSc, MSc in Electrical Engineering, National University of Colombia
Born February 24, 1971
Citizen of Bogotá D.C., Colombia

Composition of the Jury

Professor Dr. A. Wokaun - Examiner
Professor Dr. E. Jochem- Co-examiner
Mr. S. Kypreos - Co-examiner

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Abstract

Being technology a fundamental driving factor of the evolution of energy systems, it is essential to study the basic mechanisms of technological change and its role in achieving more efficient, productive and clean energy systems. Understanding its dynamics constitutes a guide for policy formulation and decision-making and the conception of effective intervening instruments. Technology development does not occur as an autonomous independent process, but evolves from a number of endogenous interactions within the social system. Technologies evolve and improve only if experience with them is possible. Cumulative learning, both in R&D activities and the marketplace constitutes one of the basic mechanisms in the emergence and replacement of technological regimes.

Thus, efforts must be devoted to improve our analytical tools and decision-support frameworks concerning the treatment given to the technological variable. Despite its undeniable importance, several technological factors have been traditionally addressed in an oversimplified way in energy optimisation models, without recognising the cumulative and gradual nature of technological change and the important role that learning processes play in achieving cost/performance improvements in a given technology or clusters of them.

This dissertation addresses the endogenisation of some aspects of technological change in energy systems optimisation models. Here, learning curves, an empirically observed manifestation of the cumulative technological learning processes, are endogenised in two energy optimisation models: MARKAL, a widely used bottom-up model developed by the ETSAP programme of the IEA and ERIS, a model prototype developed together with other partners during the EC-TEEM project, for assessing different concepts and approaches (TEEM 1997, 1999). The incorporation of the curves provides the models with a mechanism to represent path-dependent and self-reinforcing phenomena intervening in shaping the technological trajectories of the system.

The methodological approach is described, illustrative analyses presented and insights derived from the analyses outlined. The incorporation of learning curves results in a non-convex non-linear mathematical program. Here, using Mixed Integer Programming techniques, a linear approximation to such problem is applied. When endogenous learning is present, model outcomes are significantly different than those obtained when applying static or exogenous cost trends, common in traditional approaches. New, innovative technologies, hardly considered by the standard models, are introduced to the solution. Up-front investments in initially expensive, but promising, technologies allow the necessary accumulation of experience to render them cost-effective.

The learning rates of the technologies are, however, uncertain. In order to capture this aspect, a two-stage stochastic programming approach is applied. With uncertain learning rates, a more prudent intermediate path of installations for learning technologies is followed, and a more diversified technological choice takes place. However, even under

uncertainty, technological learning in emerging technologies continues to be an important hedging mechanism to prepare for future actions. Uncertainty in many other factors also plays a relevant role in the stimulation or delay of learning. For instance, when uncertainty in emission reduction commitments is considered, the results point also in the direction of undertaking early action as a preparation for future contingencies. Early investments stimulating technological learning prove beneficial in terms of both lower costs and emissions in the long run. Increasing returns, associated to the effects of learning, and technological uncertainty emerge as interacting core mechanisms of the technological change process.

The spatial aspects of the technological learning process are also highlighted. Learning is a network phenomenon and the spatial configuration of the learning network is of considerable relevance in the scope and effectiveness of the process. Thus, the spatial scale of learning plays an important role in the global competitiveness of emerging technologies and, therefore, its variation influences significantly model outcomes. The mutual interactions between different scales of learning and several modalities of emissions trading are examined and the importance of their combined effects on the technology choice underlined. The results reveal the significant potential of international co-operation in fostering the diffusion of more efficient and clean energy technologies and the necessity of deepening the understanding of spill-over effects in the learning process.

In addition, recognising that besides market experience R&D efforts also constitute an important factor for technological progress, a simplified analysis is presented regarding the representation of this factor as part of the technological learning mechanism. A so-called two-factor learning curve is applied, where both capacity deployment and R&D expenditures contribute to the accumulation of knowledge. Although the exercise is preliminary and the formulation still depends on a meaningful statistical estimation to be supported, the analysis shows the necessity of incorporating such a factor as one of the decision variables of the models as to gain insights about the optimal configuration of R&D portfolios and continuing work on the poorly understood role and effectiveness of R&D in technological progress.

The results obtained using this modelling approach provide some important policy insights. Early investments in R&D, demonstration projects and deployment in niche markets (the so-called ERD³ strategy) of sustainable technologies, are required in order to ensure that they move along their learning curves and achieve long run competitiveness. New technologies will become competitive only if experience with them is possible. Their successful introduction requires then the promotion of innovation and learning at multiple technological, social and institutional levels. It is necessary to advance further in the endogenisation of technological change into energy planning models. The treatment given to technology dynamics affects our understanding of a number of issues concerning the future structure of global energy systems and their environmental impacts (e.g. contribution to climate change). An adequate framework is necessary to gain insights about the underlying forces that drive this evolution.

Zusammenfassung

Technischer Fortschritt ist nicht nur eine der wichtigsten Triebfedern für die Entwicklung von Produktivität und Wirtschaftskraft, er ist auch eine wichtige Voraussetzung für eine nachhaltige Entwicklung, sowohl auf lokaler als auch auf globaler Ebene. Das Verständnis der komplexen Dynamik des Fortschritts ist daher zentral für langfristige Entscheidungen in der Energiepolitik.

Die Dynamik des technischen Fortschritts muss in Energieplanungsmodellen stärker berücksichtigt werden. Eine Reihe von wesentlichen Faktoren wie z.B. die Entwicklung von Kosten und Wirkungsgraden, die Marktdurchdringung, der Einfluss von Ausgaben für F+E oder die Trägheit des Systems, sind bisher nicht oder nur als exogene Größen berücksichtigt worden. Technischer Fortschritt ist jedoch kein autonomer, sondern ein endogener Prozess, der in einem komplexen Zusammenspiel mit F+E und dem Markt abläuft. Ein wichtiger Aspekt des technischen Fortschritts sind technologische Lernprozesse.

Diese Dissertation befasst sich mit der Endogenisierung des technologischen Lernens. Es wurden Erfahrungskurven für Investitionskosten in MARKAL, ein weitverbreitetes Planungsmodell, und ERIS, einen Modellprototyp, der während des TEEM Projektes entwickelt wurde, eingeführt und die Auswirkungen auf die Struktur des Energiesystems analysiert. Die Einführung solcher Kurven in das Modell führt jedoch zu Schwierigkeiten. Die ursprüngliche, nichtlineare Formulierung der Kurven impliziert Non-Konvexitäten, die das Auffinden des globalen Optimums verhindern können. Daher muss das Problem linearisiert werden, z.B. durch die Verwendung von Mixed Integer Programming (MIP).

Das Konzept des endogenen technologischen Lernens stellt einen Schritt dar in Richtung einer umfassenderen Berücksichtigung des technischen Fortschritts in energiewirtschaftlichen Modellen. Es hilft bei der Abschätzung der Potentiale neuer Technologien sowie bei der Entwicklung einer geeigneten F+E-Politik.

Die Lösungen zeigen deutliche Unterschiede in Vergleich zum bisherigen Ansatz. Neue, innovative Technologien, die im LP-Modell kaum eingesetzt werden, erreichen hohe Anteile, wenn endogenes Lernen berücksichtigt wird. Die Ergebnisse zeigen, welche Bedeutung Pionier-Investitionen - sowohl in F+E als auch in Nischenmärkten - für nachhaltige Technologien haben. Neue Technologien können nur dann konkurrenzfähig werden, wenn sich die Kosten entlang der Erfahrungskurve bewegen und dadurch langfristig niedriger werden können.

Die Lernrate lässt sich nicht voraussagen. Um diesen Aspekt berücksichtigen zu können, wurde hier eine zweistufige stochastische Programmierung angewendet. Bei einer solchen Betrachtung, folgen die Installationen einer Technologie mit unbekannter Lernrate im Model einen vorsichtigen Mittelpfad, und eine mannigfaltige technologische Auswahl findet statt. Trotz der Ungewissheit bezüglich der Lernrate, stellt die Ausnutzung

endogenen Lernens einen wichtigen Bestandteil einer langfristig orientierten Energiepolitik dar. Ungewissheit von anderen maßgeblichen Einflussfaktoren kann technologische Lernprozesse entweder stimulieren oder verhindern. Bei unsicheren CO₂ Emissionszielen, beispielweise, vorbereitet eine frühere Stimulation des Lernens das Energiesystem für mögliche große Reduktionen in der Zukunft. Sowohl Ungewissheit als auch Lernen erweisen sich als wesentliche Determinanten des technologischen Fortschrittes.

Räumliche Aspekte haben auch Auswirkungen auf die Dynamik des technologischen Lernens. Die räumliche Skala des Lernens beeinflusst die Konkurrenzfähigkeit der neuen Technologien. Wechselseitige Einflüsse zwischen Lernprozessen und anderen räumliche Mechanismen sind auch relevant. Hier wurde die Interaktion zwischen Lernen und Emissionshandel analysiert. Solche Zusammenhänge, die von der Topologien der Lern- und Handelnetzwerke und ihre Entwicklung in der Zeit beeinflusst werden, spielen eine wichtige Rolle in der technologischen Zusammensetzung des Energiesystems und sollen in Zukunft weiter untersucht werden.

F+E Prozesse sind ebenfalls wichtig für die Stimulation des Lernens, vor allem in der erste Lebensphase einer Technologie, und müssen auch in den Modellen berücksichtigt werden. Hier wurde, als eine vorläufige Darstellung, die sogenannte Zwei-Faktoren-Erfahrungskurve eingeführt. Sie kombiniert kumulierte F+E Investitionen zusammen mit kumulierter Kapazität. Die Ergebnisse zeigen, dass die Berücksichtigung solcher Variablen in den Modellen kann hilfreich sein, um F+E Strategien zu entwickeln, die gleichzeitig flexibel und robust sind.

Da die Detailprozesse der technologischen Evolution unbekannt sind, müssen die Annahmen bzgl. des Lernprozesses gestützt und ergänzt werden durch eine sorgfältige Charakterisierung der Technologien und die Untersuchung der Haupttriebkkräfte des technischen Fortschritts.

Andere Aspekte des technischen Fortschritts sollten ebenfalls aufgenommen werden, z. B. räumliche und zeitliche Ausbreitungsmuster von Technologien. Wichtig ist auch die Untersuchung der Zusammenhänge zwischen technischem Fortschritt und der Treibhausgas-Politik, um die wechselseitigen Einflüsse von technischer Entwicklung einerseits und den Kosten von Reduktionsstrategien andererseits zu erkennen.

Eine weitergehende Integration des technischen Fortschritts in Energieplanungsmodellen ist notwendig. Die Berücksichtigung technologischer Dynamik kann unser Verständnis einer Vielzahl von Problemen erweitern: Warum entwickeln sich einige Technologien und erreichen eine dominante Position, während andere, potentiell bessere, stagnieren? Welche sind die Kosten von CO₂-Verminderungs-Strategien, und welchen zeitlichen Spielraum hat man bei ihrer Durchführung? Ein adäquates Modell ist notwendig, um Einsichten in die grundlegenden Triebkräfte dieser Evolution zu erhalten.

Introduction

Technology constitutes one of the main driving forces of economic growth (Cameron, 1996). The dynamics generated by the introduction and diffusion of new technologies into the marketplace and the improvement or decadence of the existing ones determine technological trajectories that become significant conditioning factors in the achievement of sustainable economic, environmental and social goals, both at local and global levels.

Regarding the evolution of the global energy systems, technology plays a fundamental role in their cost structure, environmental impacts, flexibility and available policy alternatives (Rogner, 1996a, IPCC, 2000). Technological trajectories condition to a large extent the resulting environmental impacts of the energy resources extraction, transformation, transportation and final use. As the concern to drive energy systems to a sustainable future path grows, technology is bound to play a very important role in the achievement of efficient and clean energy production and consumption. A transition to an environmentally compatible global energy system will very likely require changing to a different technological regime (Kemp, 1997a). Hence, the mechanisms and driving forces of the technology evolution, as well as characteristics and structure of both prevailing and emerging regimes must be understood in order to conceive the actions necessary to stimulate the change in the required direction.

Technological change heading to the de-carbonisation of energy systems, for instance, will only occur if supported by previous research, development, demonstration and diffusion of new technologies (IIASA-WEC, 1998). The successful introduction of new environmentally sound technologies into the marketplace will depend, among other factors, of the cost-competitiveness to the existing ones.

As a complex and not fully understood process, produced by the interaction of many elements, a technological path is not easily predictable. However, even with the difficulties to foresee it, a comprehensive framework for its treatment is required (Piater, 1991). The assessment of opportunities for new technologies in shaping future energy systems is a complex task involving the interaction of a number of technical, economic, environmental and social driving forces, but the understanding of such complex dynamics of technology is a central issue in policy decisions concerning the definition of future sustainable trajectories for the energy systems (Kemp, 1997a).

Technology has a dynamic, always evolving, nature (Grübler, 1998), and learning processes play a very important role in this constantly changing technological landscape. Learning is a cumulative, gradual process, which manifests itself at all levels of a society (Marchetti, 1980). Learning allows improving performance and productivity as knowledge cumulates and experience is gained through a number of sources. Technological learning has been empirically observed in many fields (Argote and Epple, 1990) and is customarily represented using the so-called learning, or experience, curves. Several examples of them

have been provided in the literature, among others for energy technologies (e.g. Ayres and Martinàs, 1992, Christiansson, 1995).

Energy systems models are employed as a supporting tool to develop energy strategies, outlining the likely future structure of the system under particular conditions and, thus, providing insights into the technological paths, structural evolution and policies that should be followed (Mattson and Wene, 1997). The manner in which the technological dynamics is considered in these models has a significant influence on the results and consequent policy decisions. There is a recognised necessity for better treatment of technological dynamics in the energy decision frameworks.

An interesting point about learning curves is that they express the fact that experience is required if a technological process is going to improve and become competitive. That is, technologies will not evolve unless experience with them is possible. This basic fact contradicts the traditional approach to handle technology in the energy analysis models. A series of factors reflecting the dynamics of technological change, such as the cost and efficiency evolution of technologies, market penetration mechanisms, the influence of R&D expenditures, the inertia and capacity of change of the system, among others, have been handled in an exogenous manner or not considered at all in the traditional modelling approaches used to examine future perspectives of the energy systems. Technological development, however, is not an autonomous but an endogenous process, where both R&D and the market intervene and influence each other (Grubb, 1997).

In linear programming models, extensively used for energy modelling purposes, technological change is customarily introduced as an exogenous factor. The cost and technical parameters of a given technology are considered either constant (static model) or as an exogenous function of time (dynamic model). These two approaches have been criticised. When considering investments costs, for instance, the static approach considers no improvements in the technology costs. In the dynamic one, the model makes use of a given technology once its costs have declined, and thus, it is not able to reflect the earlier investments, necessary to promote its successful introduction. This is the so-called “manna from heaven” approach to consider technological innovation. Cost reductions are assumed to occur at no additional cost. This approach does not recognise the need for accumulating the necessary knowledge base in order for the technology to achieve competitiveness (Messner, 1995, 1997).

A better representation can be obtained when technological change is endogenised. The incorporation of learning curves provides a more consistent model behaviour regarding the penetration of technologies into the system. When technology dynamics is endogenous, the early investments required for new technologies to achieve long-run competitiveness in the marketplace are reflected.

This dissertation presents the work of the author concerning the endogenous incorporation of technological learning in energy systems optimisation models. The endogenisation of learning curves has been performed here in two main linear programming models. The first one is MARKAL (MARKet ALlocation), a bottom-up technology oriented model

(Fishbone and Abilock, 1981), developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) and extensively used in a number of countries for national and international studies. The second is the ERIS (Energy Research and Interest Strategy) model prototype developed as a joint effort by several partners within the EC-TEEM Project¹. The methodology is described and applications of these two models are presented.

The structure of this document is as follows. Chapter 1 presents a general overview of some relevant aspects of the theory of technological change emphasising learning as one of the basic mechanisms driving the evolution of technology. Chapter 2 provides a more specific context of technological change in energy systems and describes briefly the main aspects of the evolution of some particular technologies involved in the analyses presented in subsequent chapters. Chapter 3 describes the mathematical approach to endogenise the curves in the optimisation models. Chapter 4 presents some illustrative results for a simplified representation of the global electricity generation system using both models. The structural differences between non-learning and learning models are highlighted and the influence of some parameters in the methodology are analysed with ERIS. Sensitivities to the progress ratio values and the discount rate and the effect of two-stage learning are illustrated with MARKAL. In chapter 5, an analysis of impacts of Kyoto-like CO₂ emission constraints in the global electricity generation system using the multi-regional version of ERIS is presented and the effects of uncertainty in emission constraints, demand and learning rates are examined using a two-stage stochastic programming approach. Chapter 6 is devoted to the multi-regional learning in the MARKAL model. The influence of the scale of learning in the global competitiveness of the different technologies is shown and the interaction between different scales of learning and different modalities of trade of emission permits is examined. Chapter 7 presents an attempt to incorporate R&D expenditures as an additional mechanism for accumulation of knowledge in the learning process. In chapter 8, a complementary analysis with a five-region compact model of the full energy system is carried out. Finally, chapter 9 presents some methodological conclusions, policy insights and proposals for further work. The modifications introduced to the MARKAL code for considering learning curves are listed in Appendix 1. The ERIS model is described in Appendix 2. Some examples with the single-region MARKAL model with stochastic learning rates are discussed in Appendix 3. A simplified exercise following an alternative approach to incorporate learning uncertainty in the ERIS model is presented in Appendix 4. The database built for the analysis in chapter 8 is described in Appendix 5.

Results of this dissertation have been presented in:

- Kypreos and Barreto (1998)
- Barreto and Kypreos (1999a)
- Barreto and Kypreos (1999b)
- Kypreos, Barreto, Capros and Messner (2000)
- Seebregts, Kram, Schaeffer, Barreto, Kypreos, Schrattenholzer and Messner (2000)

¹ Energy Technology Dynamics and Advanced Energy System Modelling. A project of the JOULE III Programme of the European Commission (TEEM, 1997, 1999).

- Barreto and Kypreos (2000a)
- Barreto and Kypreos (2000b)

1. Dynamics of technological change

In this chapter, a brief discussion on the dynamics of technological change is presented. The main characteristics of the process and some basic concepts are outlined. The purpose is to provide a general context for the discussion about energy technologies and the model applications presented in the following chapters and to introduce technological learning as one of the basic mechanisms of technological change. The chapter is organised as follows. First, some generalities about technology evolution are presented, emphasising the gradual and interrelated nature of the process. Then, technological learning is described in more detail.

1.1 General aspects

Technology constitutes one of the main driving forces of economic growth² and has become a pervasive factor in shaping our lives. Unlike natural resources, technology is a man-made resource with continuously increasing abundance (Starr and Rudman, 1973). Its importance grows as society evolves and new demands are continuously created, driving to opportunities for new applications of technologies and providing incentives for innovation. Technology is inherently linked to the economic and social context where it is created and evolves, being both influential in and affected by the social dynamics³. Thus, the process of technological change is not autonomous but endogenous to the social system, being linked to the existence of opportunities for innovation, the incentives to exploit them, the capabilities of the agents to carry them out and the organisational and institutional mechanisms that enable the process to take place (Dosi, 1997). It exhibits a systemic, uncertain, dynamic and cumulative nature, characteristic of socially related processes (Grübler, 1998).

Technological change can be seen as a continuous process of replacement and improvement that results from interaction and competition between new and existing technologies in the marketplace⁴. In line with the notion of society as a learning system (Marchetti, 1980),

² The importance of technical change as a determinant of long run productivity growth has been recognised since a long time already in the neo-classical economic tradition (The seminal contribution pointing out its importance is the classical paper by Solow (1957). See Cameron (1996) for an analysis of the role of innovation in economic growth). However, it remains an exogenous, unexplained variable. More recent approaches, such as the so-called "new growth" theory have devoted considerable efforts to its endogenous representation in models of economic growth. Romer (1990), for instance, incorporates a variable representing the stock of accumulated knowledge as an additional production factor in the classical production function. For a discussion of neoclassical Vs endogenous "new growth" analysis see, for instance, McCallum (1996).

³ Some authors (see, for instance, Kemp, 1997, Grübler, 1998) stress that the term "technology" should be used in a broad sense as to encompass not only the physical devices but also the ideas, procedures, know-how and social institutions involved in the process, because the effects of those different elements are difficult to separate.

⁴ Although, in some cases, a new technology providing a completely new service can create its own niche market, following a process of pure diffusion without the presence of competing technologies, normally competitors already exist.

technological change proceeds as a cumulative social learning process building upon accumulation of knowledge and experience (Nakicenovic, 1997). Thus, development requires sustained and considerable effort. Changes do not come as "manna-from-heaven". The general tendencies of the technological evolution seem to be towards higher productivity, increased output, more variety, complexity and specialisation as well as intensifying interrelatedness and interdependence between technologies (Grübler, 1998).

New technologies are likely to possess a certain advantage over the existing ones, but their economical and even technical performance may be inferior. However, while existing, well established, ones may be already in the phase of incremental improvements or even reaching saturation⁵, potential for development of emerging technologies can still be very high. Yet, costs must decrease and technical characteristics be improved in order to reach competitiveness. As experience with them is gained, they evolve, improve and can replace old technologies. The continuous improvement process, however, must be sustained by substantial investments.

The penetration of a new technology may provide a solution to problems or overcome limitations experienced with the old one. However, at the point of its introduction, there might not be awareness of the problems that this new technology will pose in the future, either due to inherent, not foreseen limitations or because its use grows to such scale that environmental or social impacts become considerable. Thus, technological change may modify the panorama of problems that will be faced in the future. New concerns will replace the old ones. In another sense, technology used as a research tool has been instrumental in identifying and understanding impacts unknown before (Foray and Grübler, 1996).

A technology goes through different stages of evolution. The literature distinguishes normally three main phases of technology development: Invention, innovation and diffusion. Invention is the first demonstration of feasibility of a solution, innovation its first practical application and diffusion the spreading and assimilation of the innovation in the socio-economic system. There can be considerable time lags between the different stages and many inventions do not become innovations, as many innovations do not reach the diffusion stage (Nakicenovic, 1997). Nonetheless, the process of innovation and diffusion should not be understood as a linear, sequential one. In fact, such linear perspective of innovation has been largely criticised. A more comprehensive approach points to a systemic model, which takes into account the existence of numerous feedbacks between the different stages (Freeman, 1996). Also, innovations do not remain static, but evolve interdependently with their diffusion. During the process, learning-by-doing and learning-by-using⁶ take place and contribute to the improvement of the technical and economic characteristics of the technologies (Silverberg, 1991).

⁵ Nonetheless, mature technologies can still improve as a result, for instance, of competitive pressures. This is known in the literature as the "sailing ship" effect (Grübler, 1998).

⁶ Learning by doing is learning through experience in manufacturing the equipment. Learning by using are the improvements of an innovation through experience gained by adopters (Cabe, 1991).

In the initial phase of development, the important goal is basically the demonstration of technical feasibility. Then, some of the initially available alternatives may be chosen and begin a diffusion process. They are spread via various communication channels (Rogers, 1983) and adopted by different social actors⁷, according to their expectations about the potential benefits of the innovation (Grübler, 1991a). Social networks, allowing interchange of information about and continuous experimentation with technologies are an essential element for the diffusion of innovations. As stated by Wright (1997), "technological change is fundamentally a form of learning, and learning is a network phenomenon". At the collective level, learning proceeds through network feedbacks between co-operative and competitive agents (Silverberg, 1991). Hence, networks encourage learning from others, stimulate compatibility and mutual dependence between actors and help, through sharing of experiences, to reduce the risk and fears of adoption of the new technology (Lahaye and Llerena, 1997).

Diffusion begins in the niche markets, where the technology may be attractive due to specific advantages or particular applications. Valuable experience can be accumulated there and performance/cost improvements may result. Early niche markets help firms to get feedback from the experience of the users and to demonstrate feasibility to potential users, manufacturers and other interested actors, such as policy makers (Kemp, 1997a). If successful, the technology may extend to other markets, eventually being able to reach a pervasive diffusion. However, successful commercialisation will depend on further performance improvements and cost reductions that ensure competitiveness. The technology evolves and matures as its markets expand. As markets are exhausted and new, possibly better, competitors arrive the technology saturates, then declines its market participation and eventually dies (Grübler et al., 1999).

Uncertainty persists along those different stages arising, among other factors, from the unpredictable nature, and sometimes even fortuitous character, of the process of invention, the existence of diverse solutions to a given problem, the difficulty of gathering and assessing information concerning the characteristics of a given technology and the inherently changing nature of these technical characteristics, as future potential of emerging technologies is not well known. That is, the dynamic nature of technology resulting from innovation activities and the process of diffusion itself constitute sources of uncertainty (Grübler and Messner, 1996). Uncertainty is, together with learning, one of the core mechanisms of technological change. Investments, both in R&D and niche markets, constitute an essential foundation of the technological change process. Actors invest in new technologies driven by their expectations that they will be more competitive and/or as a hedging strategy against uncertainty and risks (Grübler et al., 1999).

⁷ From the point of view of willingness to accept an innovation, the population of potential adopters is customarily classified as: Innovators, early adopters, early majority, late majority and laggards (Rogers, 1983). Thus, expectations play an important role in the introduction of new technologies. The differences in expectations of different actors influence the gradual dynamics of the social adoption process (Cabe, 1991). Also, imitation and copying from early adopters can be an important contributing factor to the maturation of a given technology and, in general, to technical change, seen as a collective evolutionary process (Silverberg, 1991).

The life cycle concept is very useful to describe the evolution of a technology (Ayres and Martinàs, 1992). It describes the changes a technology experiences as it passes through a series of stages from infancy and adolescence to maturity, senescence and ultimately death. As stated in their paper: "The central idea behind the life cycle concept is ageing", which can be associated with production experience. In each phase, the characteristics of the technology and the sources of technological change may be different⁸. In fact, the role of technological knowledge evolves over the life cycle. Initially, knowledge resides mainly in people's minds but, gradually, is more and more embodied in materials, equipment, procedures, standards, etc. In addition, the emphasis of R&D efforts may shift from the product to processes. Also, there is evidence that the technological learning process is a function of the life cycle. In early stages of the life cycle, production experience may be directly related to productive knowledge but, later on, as the technology becomes standardised and production processes change, this relation may become weaker.

The life cycle notion stresses the fact that improvements are gradual (typically following an S-shaped pattern), reaching a saturation as the technology approaches maturity and potential is exhausted, opening the possibility for a new emerging technology with some desirable features to grow, displacing the old one. The competition and interdependence relationships between technologies change, as the character of the markets and the technical, economical and environmental characteristics of the technology itself are modified.

Innovations are customarily categorised as radical or incremental. Incremental innovations are small, but their aggregate effect has significant long-term impacts. Such aggregate performance improvements can be characterised using the learning curve concept (described below in more detail). Radical innovations, on the other hand, are discontinuous clearly discernible breakthroughs. However, their effect is also localised, unless whole new clusters of radical innovations emerge. Profound changes normally arise from the combination of both radical and incremental technological innovations together with organisational, institutional and social changes (Grübler, 1998).

The rate of technological change depends on the diffusion of innovations and the dynamics of their adoption (Nakicenovic, 1996). In its turn, the rate of adoption of innovations is influenced by a number of factors such as compatibility with the existing environment, degree of complexity, degree to which the results of its adoption are visible to the society, etc. (Grübler, 1998). These factors are closely related to the requirements and opportunities for the knowledge and experience of an innovation to be transmitted from the early adopters to the whole society. That is, the adoption of an innovation is conditioned, among other factors, by the possibility and difficulty of learning about it.

In general, incremental innovations may diffuse faster than radical ones because they are compatible with the existing system and can take advantage of existing infrastructures, available skills, knowledge, complementary technologies etc. Radical innovations, on the

⁸ Three main sources of technological change can be recognised: New knowledge, learning and entrepreneurship and organisation (Grübler, 1998).

other hand, may require the construction of completely new systems, development and spread of a new knowledge base, constitution of the corresponding networks of actors etc. All those factors makes the penetration process more difficult and, consequently, slower (Kemp, 1997a).

Diffusion of innovations is both a temporal and a spatial process, where social networks play an important role in the successful (or not) penetration of a technology. S-shaped curves are typical for the temporal patterns of diffusion reported in the literature⁹. They illustrate the fact that innovation diffusion is a gradual process, where diversity at the micro-level drives to an ordered macro level pattern. The innovation has typically a slow initial growth rate, then growth is accelerated as new markets are reached and slows down again, as potential markets are exhausted, finally saturating. In spatial terms the innovation spreads from innovation centres to the periphery. Later adopters in the periphery are normally faster ("catch-up" process), profiting from experience of early ones, but they are likely to reach lower adoption densities (Grübler, 1991b).

A technology, however, does not develop alone but is related to and depends from others. Multiple interrelated diffusion processes contribute to the evolution. As postulated by Silverberg (1991), adoption and diffusion of technology occurs as a collective evolutionary process. The complex interactions where technologies mutually reinforce and cross-enhance each other drive to the conformation of technological regimes¹⁰, the creation of technological clusters (Sahal, 1983), that is, families of technologies evolving and diffusing together, and the constitution of associated networks of economic and social actors.

The technologies conforming a cluster are related by multiple links that contribute to magnify their economic, social and environmental impacts (Grübler, 1996). These multiple relations contribute to make progress in one of them relevant, directly or indirectly, to other members of the cluster, as it helps to reinforce their own position in the marketplace. Spillover of learning accumulated for one technology may trigger improvements also in other technologies or the performance/cost advances in one of them make a whole chain of related technologies more attractive than an alternative system. Compatible changes are attracted and incorporated by the existing regime while incompatible (radical) changes are discouraged. Clusters then exhibit a self-reinforcing behaviour.

⁹ Logistic patterns have been observed for numerous technological, social and biological processes (Marchetti, 1980). The curves are a useful, though phenomenological, tool for the identification of dynamic patterns of technological diffusion and/or substitution processes. They typically appear when analysing market shares of competing technologies in a market (Grübler et al.,1999). See, for instance, Marchetti and Nakicenovic (1979) for their classical analysis of the competition of primary energy carriers or Nakicenovic (1991), for an analysis of the dynamics of substitution of transport infrastructures. In those cases, the analyses revealed the regularity and self-consistency of the rates of change of energy and transport infrastructures during long periods of time. Change in those infrastructures appeared as a gradual process with very long time constants.

¹⁰ Defined as the set of knowledge, practices, processes, organisations, infrastructure, resources etc. making up a technology (Kemp, 1997a).

1.2 Path dependence and "lock-in"

Technological progress tends to follow certain "trajectories". That is, ordered patterns of change that, once set up, may be difficult to alter. This is referred to in the literature as path dependence. The system follows a sequence of advances that favour certain groups of technologies above others, thus making difficult the emergence of radically new options (Kemp, 1997a). The trajectory is basically founded on incrementally augmenting knowledge bases, which constrain the possible directions of search and the opportunities for innovative advances (Dosi, 1997).

Several factors intervene in the emergence of such persistent patterns. The existence of clusters and regimes is one of the forces making change more difficult, contributing, together with other factors, to the system's inertia to follow alternative trajectories. Cumulative learning effects also contribute to the rise of a dominant technology, or cluster of technologies, and its entrenchment into the socio-economic system¹¹. The dominant technologies benefit from evolutionary improvements, established procedures, norms and production systems, better understanding and acceptance, etc.

Related to the (macro) notion of path dependence is the concept of "lock-in". Technological "lock-in" may be described as a particular historical technological choice that is very difficult to reverse (Arthur, 1988). As a technology becomes dominant in a certain market sector, it is able to increase its comparative advantage, by means of cost/performance improvements, interrelatedness with complementary technologies and the build up of infrastructure and a network of associated social actors, conforming a whole technological regime which will be difficult to challenge and displace (Kemp, 1997b). Technological learning, together with links between different technologies and different industries play an important role in the development of a "lock-in" situation (Cowan and Hultén, 1996).

The phenomenon of "lock-in" is related to the property of increasing returns to adoption exhibited by some technologies. The more a technology is adopted, the more experience is gained and the more it is improved, driving to its further adoption (i.e. the probability of adoption increases with the share of the market). Different sources for increasing returns to adoption can be identified: Learning effects, economies of scale, network externalities, technological interrelatedness, and information. Increasing returns act as a self-reinforcing cumulative mechanism. Thus, when a dominant technology emerges, it may become progressively "locked-in". A positive feedback loop is provided between experience and imitative diffusion profiles (Criqui et al., 1998).

Non-predictability is also associated to the presence of increasing returns. Small random¹² historical events, which may provide an initial advantage to a given technology, could cumulate and be magnified as the adoption process takes place, such that this technology

¹¹ The development of a technology requires organisational structures, as well as skills and know-how of the different economic agents involved, which represent a kind of individual and organisational learning that can be very specific to a particular trajectory (Silverberg, 1991).

¹² In the sense of events outside the ex-ante knowledge of the observer (Arthur, 1988).

reaches a dominant position in the market, "locking out" competing ones (Arthur, 1988). Thus, early historical events may influence the prevailing solution.

As the positive feedback mechanism drives to the amplification of the effects of initial small events, multiple outcomes of the adoption process are possible. In fact, unlike the single equilibrium point solution implied by the assumption of diminishing returns customarily used in conventional economic analyses, the problems of allocation under increasing returns may exhibit multiple equilibria¹³ (Arthur, 1990). A central problem arises as how to determine which equilibrium will be selected over time.

In addition, under increasing returns the possibility of an inefficient result from the adoption process exists. There is no guarantee that the outcome will be the "best" one (Arthur, 1990). An inferior (from an ex-post perspective) alternative with lower long run potential may be chosen, being used and improved accumulating an economic advantage. Preference for this, initially attractive but slow to improve, technology can lock in the market to this option. This alternative may result inferior in the sense that if other technology with higher improvement potential would have been picked up and developed, it could have achieved better cost and/or performance characteristics in the long run. Thus, as the best options will not necessarily be selected by the system, diversity of alternatives in the early phases of development is highly desirable. Diversification becomes the optimal response against technological uncertainty (Messner et al. 1996, Grübler and Messner, 1996).

The existence of so-called "network externalities"¹⁴ also contributes to the stability of the dominant path. As mentioned before, network externalities arising from the growth of a system are one kind of increasing returns to adoption. Complementarity and compatibility between the co-evolving components of the network are key factors for the existence of such externalities.

The externalities create a positive feedback effect as they provide incentives for the adoption of the same (or a compatible or complementary) technology and then tend to coordinate the actions of different economic agents, favouring particular technological systems. They typically arise in relation to infrastructures¹⁵ (Grübler et al., 1999). Their existence may pose barriers for the entrance of new, radical technologies, which are not compatible with existing network infrastructures. If a new technology requires the deployment of new infrastructure networks in order to operate, high initial costs and compatibility issues will difficult or delay its deployment. Network structures, where strong

¹³ The existence of multiple equilibria is also related to the notion of non-convexity. For non-convex systems several minima will exist and historical "chance" may determine which of those is finally reached (Arthur, 1990).

¹⁴ Network externalities arise when "the utility that a given user derives from a good depends upon the number of other users who are in the same network" (Katz and Shapiro, 1985). As costs are shared among all the network users, but they obtain the full utility, the real value of the service is exogenous to the price they pay to access it (Grübler, 1998).

¹⁵ Energy, transport and communication infrastructures are typical examples.

complementarity and interrelatedness among technologies exist, contribute to the creation of technological clusters.

Mechanisms to reverse "lock-in" are of importance for technology policy issues. This is relevant, for instance, when significant environmental impacts have been realised with the existing technology or are expected to occur in the future and, therefore, the introduction of alternative technologies would be desired/required. However, overcoming "lock-in" and path dependence can be a difficult task. It is not sufficient for the new technology to be "better" than the established one. Cowan and Hultén (1996) mention six factors that could possibly contribute to "escaping" from a "lock-in" situation: Crisis in the existing technology, regulation, technological breakthroughs producing cost reductions (or raising the expectations of doing so), changes in consumer taste, niche markets and scientific results which put some pressure on the old technology or provide new knowledge about the new one. On the other hand, the "lock-in" phenomenon could be exploited in the introduction of new technologies with desirable characteristics.

Thus, a number of sources may contribute to self-reinforcement of a particular technological trajectory, being the emergence of dominant technologies dependent, among other factors, on accumulated knowledge, cost and performance improvements, build-up of accompanying infrastructure and complementary technologies, human adaptation patterns and embedding into the economic and social system (Kemp, 1997a).

However, even if reinforcement of particular technological directions in the economic and social systems is strong, major technological shifts may occur on the long term. But, as path dependence is difficult to overcome, technological change takes time, particularly when dealing with radical changes that require a transition to a new technological regime. Substitutions in energy or transport infrastructures and systems, for instance, may have very long time constants (several decades, or even centuries). But, also as a result of the interrelatedness and mutual dependence, when changes occur, they are likely to be pervasive.

Nonetheless, changes of the technological trajectory imply uncertainty, specially because the future characteristics of competing technologies are unknown and future extension of their applications range (that is, market opportunities) and capabilities may depend on the unforeseen development of complementary technologies and will unfold as part of an interdependent process (Wright, 1997). Even more, the developments may depend on expectations and commitment of different social actors. Thus evolution occurs as actors balance their perceived risks and opportunities with the new technologies, and adopt strategies to face them. Learning, a basic mechanism to seize technological opportunities and reduce their uncertainty is one of such strategies.

1.3 Technological learning

Learning processes have been long recognised in psychology and management science to play an important role in the performance of individuals and organisations¹⁶. They have also been identified in many different social and economic activities, driving to the conception of the society as a learning system (Marchetti, 1980). Learning is, indeed, a key driver of technological change and diffusion of innovations. In this section, a brief description of the learning curve concept is presented, which represents an empirical manifestation of learning processes within the technological context, central to the analyses performed in this work.

A learning¹⁷, or experience, curve shows how experience improves performance in a given activity. Thus, a generic learning curve relates a certain performance index to a quantity measuring cumulated experience (Robinson, 1980). The most common specification (and the one applied here), however, describes the specific investment cost of a certain technology as a function of the cumulative capacity, which is used as a proxy for the cumulated knowledge. The curve reflects the fact that some technologies may experience declining costs as a result of increasing adoption into the society, due to the accumulation of knowledge by, among others, learning-by-doing, learning-by-using and learning-by-interacting processes.

The experience curve represents the aggregate effects of incremental, minor but sustained changes, which, when compounded, are important drivers of technological progress. Change of this nature takes place as an evolutionary process involving significant experimental effort. It proceeds in a cumulative way as the stock of practical experience grows (Sahal, 1980).

Technological learning is one of the processes where increasing returns, already discussed above, are present. The more experience is accumulated with a technology the better its performance/cost ratio may become and the more likely that further adoption of the technology occurs (Isoard, 1996). The curve, thus, provides a representation of this self-reinforcing, positive feedback effect.

¹⁶ When discussing learning in the context of management science, De Geus (1997) sees it as "the capability to shifting and changing, developing new skills and attitudes...The essence of learning is the ability to change one's internal structure to remain in harmony with a changed environment". There is a direct parallel between this and the idea of technologies continuously changing in order to adapting to ever-increasing requirements and new needs in a competitive environment.

¹⁷ Human learning, in the sense of improvement or creation of new skills of the labour force, although important, is but one of the many different intervening factors that manifest in a cost reduction or performance improvement. Also, although learning and economies-of-scale are different phenomena, in the practice their effects overlap and are very difficult to separate (Wene, 2000). Therefore, here it is assumed that the experience curve may contain also scale effects, among others. The learning curve concept should be regarded as a useful model that embraces and aggregates a number of factors participating in the improvement of costs or technical characteristics of a given technology.

The customary form to express an experience curve is using an exponential regression (Argote and Epple, 1990):

$$SC(C) = a * C^{-b} \quad (1)$$

Where:

- SC: Specific cost (e.g. US\$/kW for electricity generation technologies)
 C: Cumulative capacity
 b: Learning index
 a: Specific cost of the first unit

The learning index b defines the effectiveness with which the learning process takes place. It constitutes one of the key parameters in the expression above. Usually, its value is not given but the progress ratio (or the learning rate) is specified instead. The progress ratio (pr) is the rate at which the cost declines each time the cumulative production doubles. For instance, a progress ratio of 80% implies that the costs are reduced to 80% of their previous value when the cumulative capacity is doubled. The relation between the progress ratio and the learning index can be expressed as:

$$pr = 2^{-b} \quad (2)$$

An alternative is to specify the learning rate (lr) defined as:

$$lr = 1 - pr \quad (3)$$

The parameter a may be computed using one given point of the curve (usually the starting point SC_0 , C_0 is specified) as¹⁸:

$$a = SC_0 / (C_0)^{-b} \quad (4)$$

The curve is very sensitive to the progress ratio specified and to the starting point (SC_0 , $C_{k,0}$). The future progress ratio of a given technology can be uncertain. Also, the definition of the starting point may pose difficulties for future, or currently in the pre-commercial stage, technologies for which data concerning actual cumulative capacity or costs may not be available or reliable.

As an illustration of the sensitivity to its defining parameters, Figure 1 presents an hypothetical learning curve with different values of the progress ratio (0.81, 0.85, 0.90) but a common starting point ($SC_{k,0}=5000$ US\$/kW, $C_{k,0} = 0.5$ GW). An additional curve with PR=0.85 but a different starting point ($SC_{k,0}=5000$ US\$/kW, $C_{k,0}=2$ GW) is also presented in this figure.

¹⁸ The curve could also be expressed as: $SC(C) = SC_0 * \left(\frac{C}{C_0}\right)^{-b}$

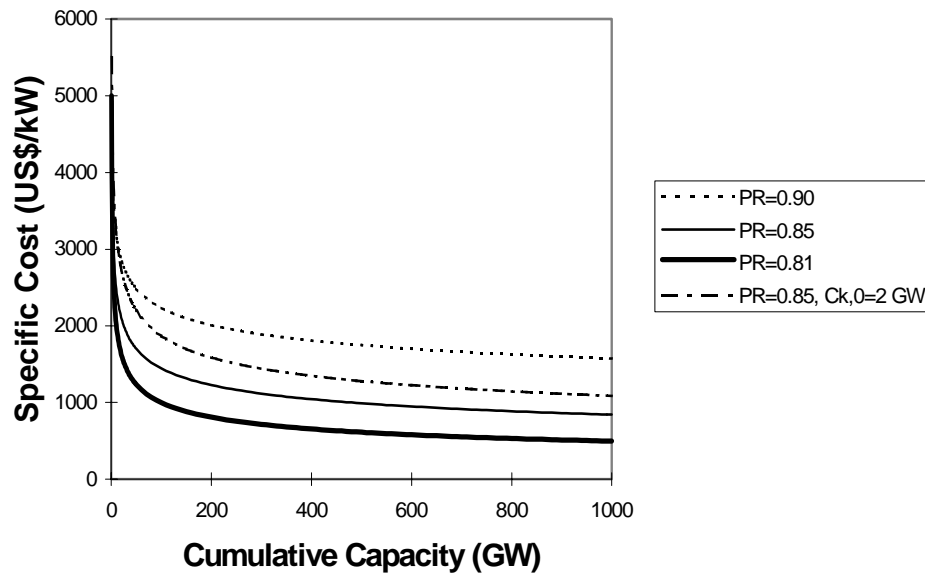


Figure 1. *Learning curves. Different progress ratios.*

The conventional form of presenting experience curves is in double logarithmic scale, where they become straight lines. As an example, Figure 2 presents a comparison of the learning curves of wind turbines and solar PV modules estimated by Criqui (2000) with that of gas turbines (MacGregor et al., 1991 and IASA-WEC, 1995). The curves are estimated at the global level. The comparison shows that, although starting from much higher values, the two renewable electricity generation technologies are experiencing a vigorous dynamics of learning, similar to that experienced by the gas turbines in the past.

The linear form in the logarithmic scale should not drive to the interpretation that ever decreasing costs can be expected. In fact, with every consecutive cumulative capacity doubling, the cost reduction obtained is smaller than in the previous one. In addition, every new capacity doubling is more difficult to obtain over time as the technology approaches its maturity and markets are exhausted. Also, the existence of limits to the experience curve has been pointed out (Bodde, 1976), due to factors such as product obsolescence, which does not make reasonable to explore lower cost regions of a product that does not anymore respond to market needs or trends, or increasing inflexibilities in the production process, which may prevent the implementation of the changes necessary for further improvements.

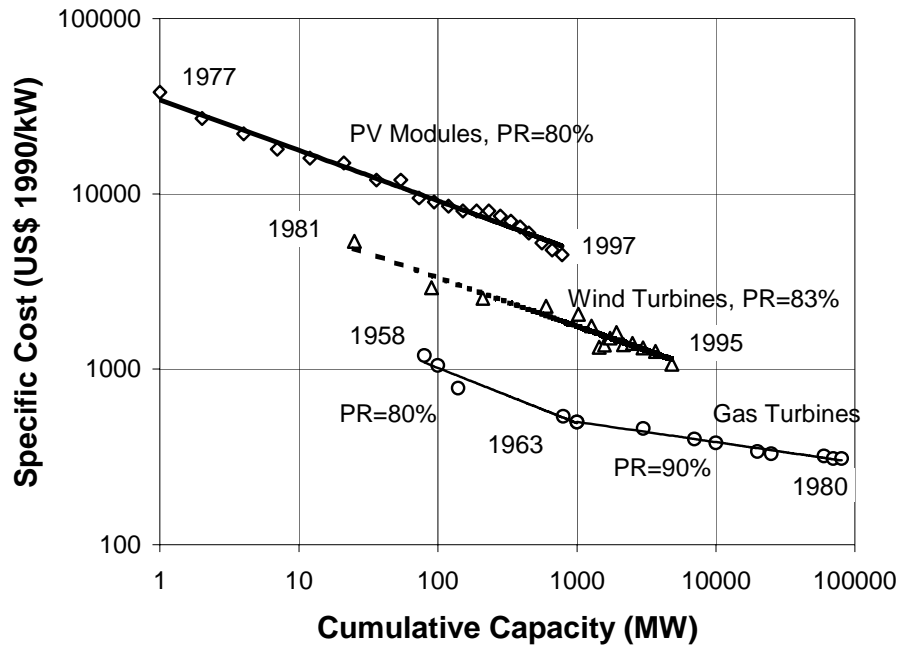


Figure 2. *Learning curves for different energy technologies.*
 Data Sources: PV modules and wind turbines: Criqui (2000). Gas turbines: MacGregor et al. (1991) and IIASA-WEC (1995).

Learning has many different sources, such as production (learning-by-doing), usage (learning-by-using), R&D efforts and interaction with other social actors (learning-by-interacting), among others (Grübler, 1998). There are a number of technical, social, economical, environmental and organisational factors, which influence the presence (or absence) and rate of technological learning processes.

Learning-by-doing processes in manufacturing, for instance, have been long recognised in the literature (Argote and Epple, 1990). Productivity increases occur as organisations gain experience in production. Organisational improvement constitutes a source behind the experience effect, driven by a number of forces such as labour efficiency increases, new processes and changes in production methods, changes in the administrative structure, modifications of the product itself, etc. (Bodde, 1976). Different organisations learn at different rates. Factors such as organisational "forgetting"¹⁹, employee turnover, knowledge transfer from other products and organisations and the presence of economies of scale affect the learning rate (and/or its estimation) of a given organisation (Argote and Epple, 1990).

¹⁹ Knowledge acquired through learning-by-doing may depreciate driving to a variation of the organisational learning rate. Argote and Epple (1990) mention the case of production of the Lockheed's L-1011 Tri-Star aircraft as an example of such organisational "forgetting". This reveals the necessity of preserving human know-how as one of the requisites for realising technological learning.

Learning-by-using, on the other hand, is generated by the utilisation of a product or process by the final user (Criqui et al., 1998). Experience with a product helps to understand its performance and limitations, define optimal schedules and procedures for maintenance and repairing, and learn about the real user needs. Also, it allows to carry out modifications or re-design or to suggest them to the manufacturer (Habermeier, 1990).

The last point drives us to the learning-by-interacting process, where communication between producers and users of the product plays a very significant role in achieving efficient product improvements and increasing the associated knowledge base, as firms are able to exchange information about product characteristics and user requirements generated during the learning-by-doing and learning-by-using processes (Habermeier, 1990). Also, the interaction among users and manufacturers contributes to the creation of network arrangements that facilitate the communication flow and allow the firms to benefit from external sources of learning²⁰.

Evidence of learning in many different industries, processes and activities has been collected, and learning curves have been applied to different kinds of analysis. Although their existence has been well known for many decades²¹, only in the early 70's they began to be recognised as a useful planning and management tool (Conley, 1970, Cunningham, 1980). The concept of the experience curve has proven helpful when defining product-marketing strategies of the firms, making use of the powerful relationship existing between cumulative volume of production, market share and profitability (Bodde, 1976).

The learning curve has, however, a phenomenological nature, in the sense that the experience effect can, but not necessarily will, become manifest in a given situation. Thus, learning curves do not exist for all the technologies²². A number of forces must intervene to make the curve operational. In particular, it is clear that deliberate and continuous efforts are fundamental. Without them the learning potential of a given activity (or technology) would not be "tapped", knowledge will not be accumulated and the curve may not materialise.

Being affected by a number of interacting factors at different levels, the progress ratio, one of the key parameters of the curve, is highly uncertain. Its future value for a given technology is difficult to predict, and it is unsure how will it change along the lifetime of the technology. While historical estimates provide valuable information about learning

²⁰ Criqui et al. (1998) mention advances in scientific knowledge, the interface between science and technology, knowledge embodied in people and equipment, contracting for R&D and buying patents and licenses as important external sources of learning, which, however, must be combined with internal learning activities of the firm in order to become effective.

²¹ Wright (1936) was the first to report the experience effect in the manufacturing of airplanes.

²² Conventional nuclear and coal electricity generation technologies are frequently cited in the literature as examples of technologies whose costs, due to a number of factors (basically design changes motivated by safety and environmental concerns), have increased, rather than decreased with cumulative production. Thus, when it comes to costs their learning rates may be negative. However, learning may have manifested in other indicators of performance such as the conversion efficiency of the plants or safety. In other cases, however, as discussed by Argote and Epple (1990) or Grübler (1998), "forgetting by not-doing" may occur, where accumulated knowledge is, at least partially, lost, driving to an increasing cost trend.

trends, it is not possible to foresee if the observed trends will continue in the future or new developments will cause an alteration of the learning trajectory. The extrapolation of initial trends could drive to an overestimation or underestimation of the progress ratio. Underestimation of the progress ratio represents a risk as investments in a given technology may turn out to be more costly than expected, affecting the competitiveness of the actors involved. Overestimation, on the other hand, will alter their profitability margins (Grübler and Gritsevskiy, 1997).

Schrattenholzer (1998a) illustrates the variability of the progress ratio using the example of several energy technologies. Depending on the data sets, time spans and performance indicators (e.g. prices instead of costs) being considered, different estimates are obtained. Also, in his analysis, some technologies were shown to experience declining learning rates over time. The uncertainty inherent to the progress ratio highlights the need to provide, if possible, a stochastic treatment for this parameter. Such possibility will be discussed in more detail below.

Despite the uncertainty, efforts have been devoted to establish typical ranges of variation of the progress ratio for different technologies and processes. Argote and Epple (1990) reported learning rates for a number of industries and products. In their sample, the bulk of progress ratios range between 56% and 100%, with a median value of 80%.

Also, some efforts have been made to derive criteria for taxonomical classifications, where typical progress ratios could be assigned. Christiansson (1995) presented an analysis of progress ratios following one of those stylised taxonomies. Such taxonomy considered three main types of plants according to the production processes involved (big plants, modular plants and continuous processes²³), identifying higher learning potential for the hybrid continuous operation processes, which combine characteristics of both big and modular plants.

On a related aspect, it has been postulated that a possible dependence of the learning process on the technology life cycle may exist (Ayres and Martinàs, 1992, Nakicenovic, 1997). Different stages in the life of a technology could be associated to different speeds of learning.

Typically, in an R&D intensive phase the technology may experience steeper cost reductions than in the commercialisation phase (Christiansson, 1995). However, Ayres and Martinàs (1992) show some examples where the contrary effect occurs. They explain this with the argument that, in the initial stage, achieving technical feasibility was the priority, but when the technologies began to be commercialised, cost reductions became critical. Thus, learning rates not necessarily will be reduced when technologies go to the

²³ "The categorisation is based on the parameter economies of scale... The big plants category represents economies of scale due to scaling up of units..., module technologies represents economies of scale due to mass production of identical units..., and continuous processes combine the scaling effects of big plants with those of modules (representing continuous process for the production of standardised commodities in large-scale units)" (Neij, 1997, see also Christiansson, 1995).

commercialisation phase. Nonetheless, as a guide, a stylised typology of technological development has been proposed by Grübler et al. (1999), where the learning rate declines as the technology proceeds from infancy to maturation and ultimately senescence stages. Such typology could be useful to reflect the relationship with the technology's life cycle.

Although simplified, the establishment of stylised taxonomies of the learning rates of technologies, using the type of production process involved and the life-cycle concept as guidelines, may help to define plausible ranges for the learning characteristics of new technologies or the possible future behaviour of existing ones. However, further research is required to establish which factors may affect the progress ratio and whether it varies significantly in different stages of the life cycle for a given technology. At this point, it has to be noticed that, when analysing several competing learning technologies, it is not only the absolute form of each learning curve, but their relative ranking what matters (Robinson, 1980).

The curve conveys an important message for energy policy regarding the need of continuous experience in order to stimulate the development of new technologies. In fact, the experience curve constitutes a powerful tool for strategic decisions in energy technology policy. It can be used as a guide to define which emerging technologies appear as the most promising (i.e. have bigger potential to become cost-competitive in the future) and the amount of investments required for making them competitive. This may help to define a portfolio of alternatives on which efforts and resources should be concentrated and establish where, if necessary, should public resources be allocated most effectively to support their development and deployment.

An important concept associated to the experience curve is the maturation cost. The maturation cost corresponds to the cumulative investments necessary for the break-even of a given technology. The maturation costs provide an estimation of the amount of resources (learning investments) that must be invested in a given technology under given learning conditions in order to make it competitive in the market. Figure 3 illustrates a "static" representation of the maturation cost concept, where a given fixed cost level is assumed to be the competitiveness threshold. In reality, however, a dynamic competition process takes place. The competitiveness threshold is most likely not a fixed value but is represented by the learning curve of the mature dominant technology.

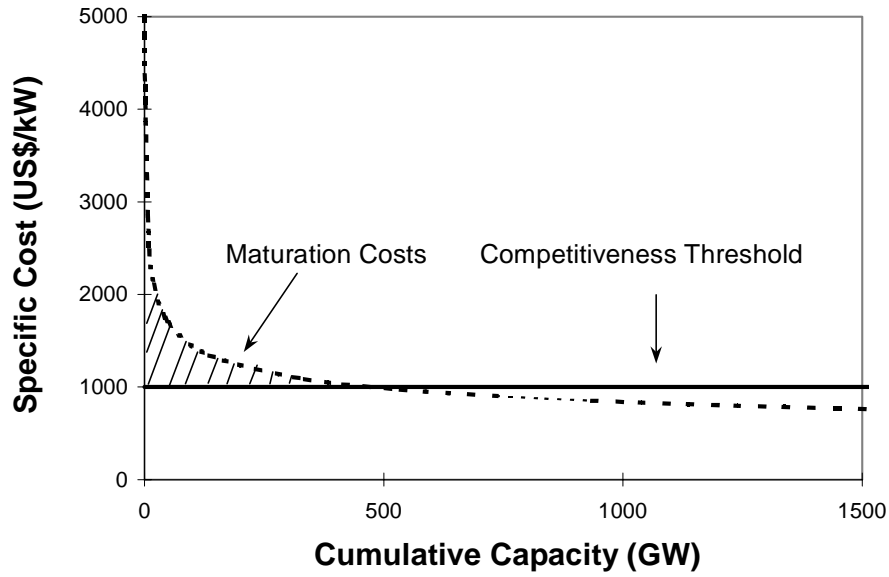


Figure 3. *Maturation costs for a learning technology.*

Learning investments should, however, be chiefly provided by market actors. Thus, the main role of policy should be that of conceiving instruments to support and facilitate such market learning. Nonetheless, public intervention and deployment may still be required at the first stages of commercialisation to stimulate the investments of other actors or when long-term benefits can be expected but are not captured by the short-term perspective of private investors. In such cases, the experience curves are helpful in defining the appropriate stage at which public support should be applied and withdrawn.

In addition, awareness of the experience effect is important when designing mechanisms to foster the penetration of new technologies into the marketplace, such as market transformation programs²⁴. Stimulation and exploitation of learning processes should be at the core of the deployment strategies conceived within such programs. Also, the creation of networks of actors should help to multiply learning opportunities both in manufacturing and use of the technologies.

1.4 Summary

Technological change appears as a complex, uncertain and dynamic phenomenon of high relevance both for economic and social development. As it arises from within the socio-economic system, it is an endogenous rather than an autonomous process. This nature must be emphasised in models dealing with technology dynamics.

²⁴ "A market transformation programme is a strategically planned approach, based on one or a combination of policy instruments, designed to effect a permanent shift in the market towards more energy efficient products and services...They are based in the understanding of the characteristics and possible markets of the technology and its interactions with different actors, policies, market conditions etc.... Market transformation programmes focus on several market actors from manufacturing to end-use" Neij (1999b).

Numerous interrelations between technologies and interactions with economic, social, technical, and environmental factors contribute to the configuration of our technological "landscape". Technologies compete in the market. Competition drives to a sequence of replacements where new, better, technologies substitute for the existing ones. The competitors, however, do not remain unaltered, but develop and improve as a consequence of innovative actions and the diffusion process itself.

Learning processes together with uncertainty appear as core mechanisms of the technological evolution. Technological change can be seen as an evolutionary cumulative learning process building upon accumulation of knowledge and experience. Deliberate and sustained efforts are required in order to stimulate the acquisition of relevant experience and the preservation of the knowledge associated with a given technology, which allow achieving cost and performance improvements, vital factors for its survival in the marketplace. The learning, or experience, curve appears as a useful model to represent the aggregate effects of such evolutionary progress. Many technical, economic, environmental and social factors, however, influence the magnitude of learning rates. Thus, the future evolution of the learning trends for a given technology is uncertain.

Technologies co-evolve in clusters, formed when related and complementary technologies reinforce and cross-enhance each other. As clusters evolve, infrastructures are built, networks of associated social actors are created and knowledge is accumulated. A technological trajectory emerges as this path dependent process take place.

A number of cumulative and self-reinforcing effects make prevailing technological trajectories difficult to alter. The system exhibits inertia, i.e. an opposition to alter its direction. Even more, the system can follow trajectories that may not be optimal but where the high costs of changing to another path prevent a different technology choice. Incremental changes, taking advantage of the compatibility with the existing paradigm are easier to introduce and diffuse faster. Radical changes, on the other hand, take time. New infrastructures must be deployed, accumulation of knowledge must be pursued, new networks of social actors must emerge, organisations and institutions created, etc. Early efforts must be devoted to prepare the long-term transitions. As a supporting activity, sound conceptual and analytical frameworks must be developed in order to deepen our understanding of the possible technological dynamics and intervening mechanisms (e.g policy) and explore their consequences, so as to orientate such early actions in the adequate direction.

2. Technology dynamics in energy systems

After having described some of the main characteristics of the technological evolution in the previous chapter, in this chapter the discussion focuses on such patterns and mechanisms of change as they manifest in the energy systems. Understanding the dynamics of energy technologies is essential to identify the possible future evolution and conceive sound policy measures to reorient the system. Here an exhaustive analysis is not intended and only some relevant aspects will be highlighted.

The chapter is organised as follows: First, a general discussion illustrates the systemic character of the energy system, emphasising the role that cumulative learning processes play on its evolution. Then, the relevance of the technological variable in the policy debate about the role of energy systems in global climate change mitigation is discussed. Finally, a brief description is made of the main developments of some energy technologies that might play a role in the transition towards a more efficient, productive and clean global energy system.

2.1 General aspects

Sustainable development depends, among other factors, of cost-effective, safe and environmentally sound energy systems (Brundtland Commission, 1987). Technological advance is a key factor in this process as it enables a more productive use of energy resources. Improvements in energy and material efficiency and de-carbonisation of energy sources contribute to the transition towards a sustainable pathway for the global society. The achievement of these goals, however, requires the emergence of innovative, highly productive and environmentally compatible technologies. Very complex processes of technological, economic and social dynamics will affect the evolution of these technologies and their successful incorporation to the energy systems. Thus, it becomes very important both to develop a more profound comprehension of these processes and to incorporate them into the corresponding policy and decision-making frameworks.

Continuous technological change has been a major driver of the structural transformations of the energy systems. The comparative advantages of new energy sources and the emergence of new applications for them in form of new end-use technologies have been important drivers for the replacement of old predominant ones. A competitive substitution process has continuously taken place in the energy system (Marchetti and Nakicenovic, 1979). As a whole, the system has become more productive, consistently evolving towards the use of commercial forms of energy and more convenient, flexible and clean energy carriers. Also, long term trends of improvement of aggregate energy intensities and rising efficiencies are evident (IIASA-WEC, 1998).

Levels of energy use are strongly related to the economic activity. Economic growth, also substantially driven by technical change, implies increasing energy needs and requires the provision of new energy services. Technology has an important role in de-coupling energy

demand from economic growth by increasing the efficiency of production, conversion, transmission and distribution and final use of energy. A substantial potential for efficiency improvements at all stages of the energy system still remains to be exploited (Nakicenovic et al., 1996a, Jochem, 2000).

Environmental concerns and constraints, which have been mounting in the last decades, are another powerful driving force in the energy systems. Energy production, conversion, transportation and use have a number of impacts at the local, regional and global levels. Environmental effects range from local and regional air pollution and acid deposition to deforestation, potential radioactive hazards and emissions contributing to the greenhouse effect at the global scale (World Bank, 1997). Environmental constraints act as an inducing factor of technological change. They may stimulate the creation of technology breakthroughs and help to redirect the development paths to alleviate actual and potential impacts.

The fulfilment of growing energy needs with less environmental impacts requires cleaner energy carriers and more efficient systems (IIASA-WEC, 1998). This is particularly important for developing countries, which may experience a highly dynamic growth of their energy requirements and face the challenge of meeting their development goals while reducing environmental damage. Technological progress plays a key role in reducing the environmental impacts of energy. Increasing efficiency and shifting towards less polluting sources, conversion technologies and end use devices help to lessen the environmental burden imposed by energy-related activities. Technological change can thus be seen as an enabling instrument to achieve sustainable energy systems.

A particularly relevant example of such role of technology is the continuous, although slow, global trend towards decarbonisation, i.e. the reduction of the carbon content of the energy supply mix. Such evolution has been driven by technological change in energy supply and end use (Nakicenovic, 1996). The progressive, and ongoing, de-carbonisation process has proven to be characteristic of the historical evolution of the global energy system. It has accompanied the increase of our knowledge to handle energy.

Decarbonisation can be seen as a cumulative learning process (Nakicenovic, 1997), where the system has progressively been able to deliver less carbon for each unit of energy supplied²⁵. Through cumulative technology improvements and learning, it has gradually reached a higher environmental productivity. However, current concerns about the future impacts of the energy system may require decarbonisation to be accelerated, as to compensate increases in energy supply requirements and thus prevent a strong increasing trend of the corresponding emissions. Such process, that in the future could also drive to reductions in the intensity of material use in the energy sector, appears to be compatible with the emergence of new environmentally sound energy supply and demand technologies.

²⁵ The corresponding learning curve can be expressed as carbon intensity of the economy (kg C/unit of GDP) Vs Cumulative GDP (Nakicenovic, 1997).

A third driving force is the institutional and organisational framework of the energy sector. The evolution of the institutional and regulatory environment in which the actors operate also affects the particular technological paths being followed and the rates of transition. A given institutional framework may tend to favour some technologies more than others. For instance, the deregulation of the electricity industry which has incorporated new private actors, has favoured the choice of technologies with lower capital costs, faster construction cycles and shorter periods for return of investment, such as the gas turbine, driving, in some cases, to the so-called “dash for gas” (EIA, 1996). Also, dynamic organisational transformations in the oil industry, which have emphasised a vertical integration of the firms and a higher concentration of the industry, through mergers and/or acquisitions, are linked to the improvements in drilling, refining and oil recovery processes as companies were forced to lower their exploration and production costs in order to remain competitive in an environment of fluctuating prices and increasing competition.

The institutional environment also influences the access to knowledge, the type of learning and expectations and perceptions of the future. Firms with different learning structures may generate different innovation patterns. Also, “the paths are influenced by the beliefs and perceptions about the future that inspire technological expectations of firms” (Martin, 1996).

The institutional aspect has important implications because penetration of new technologies requires up-front investments, both in R&D and in deployment of demonstration projects and commercial applications in niche markets. These investments in the learning process of promising, but still expensive and imperfect, technologies may produce long-term returns, once they achieve competitiveness, but could be regarded as unattractive in liberalised energy markets where short-term revenues are the main decision criterion (IIASA-WEC, 1998).

Technological change in energy systems exhibits a highly systemic nature with cumulative learning processes, technological interrelatedness and infrastructure requirements playing a fundamental role in the pace of change and the directions the system follows (Martin, 1996). There are multiple links and interrelations between resources, technologies, infrastructures as well as the institutional schemes, organisations and, in general, actor networks built around them. These factors interact and reinforce each other, creating a technological regime extending along the whole energy chain, from primary resources, conversion technologies and transportation and distribution infrastructures to end-use devices (Kemp, 1997a). The existence of such a regime conditions to some extent the possible directions of technical advance and contributes to the “lock-in” to existing dominant technologies.

The current global energy system, following a path mainly based on fossil fuels, is said to be “locked-in” to a technological regime of hydrocarbon resources and corresponding conversion and end-use technologies, which makes difficult for alternative resources and technologies to penetrate (Kemp, 1997b). One of the reasons for the persistence of such trajectory is that technological learning outside the hydrocarbons sector has been limited or imperfect. At the same time, significant advances have been incorporated into hydrocarbon-

based technologies such as gas turbines and oil drilling platforms (Martin, 1996). Development of alternative fuels and technologies has faced a number of barriers, financial, for instance, in the case of synthetic fuels or social in the case of nuclear reactors.

Also, the infrastructures in place, with a number of associated network effects, tend to enhance a given regime. A typical example is found in the transportation sector, where the penetration of alternative fuel vehicles is hindered, among other factors, by the lack of the corresponding infrastructure for the fuel transportation and distribution (Thomas et al., 2000). In addition, energy systems are capital intensive and, as many energy investments and associated infrastructures have long lifetimes, capital turnover rates are slow. Thus, as a result of the combination of a number of factors, energy systems possess a considerable inertia that tends to increase the costs of fast transitions in the system (Grubb et al., 1995). Therefore, change in energy systems is slow, spanning through decades or even centuries.

Thus, being the trajectory of the system constrained to some extent by the gradually evolving and path dependent conformation (and replacement) of energy technology regimes, near term actions that can initiate long-term changes may have critical importance. Here, one of the main conclusions of the IIASA-WEC (1998) study on the future of the global energy system may be relevant. Across the different scenarios, the study found a consistent pattern towards cleaner and more flexible final energy carriers. However, the corresponding supply patterns could diverge substantially in the long term. As noted by Grubler (1999), the long term configuration of the system is, among other factors, a matter of technological choice, where the preconditions for a long term departure from, or reinforcement of, the current trajectory will be created by the RD&D efforts, intervening investments and technology diffusion strategies of the next 20 years.

Lack of learning opportunities for technologies outside the dominant hydrocarbon regime may have as a consequence that the bulk of knowledge accumulated, organisational and institutional structures and actor skills and expectations tend to lie inside the boundary of the current paradigm. In order to emerge, learning of new technologies must be faster than that of established ones. Thus, learning opportunities for emerging energy technologies must be fostered by policy measures and market mechanisms. This is related, for instance, to the necessity of creating and exploiting niche markets. Early niche markets provide good learning opportunities (both for suppliers and users) and consequent cost/performance improvement of emerging technologies, understanding the user needs and help to resolve uncertainties surrounding the viability of radical technologies.

In summary, given the systemic, cumulative and self-reinforcing nature of technological change and the consequently slow rate of change in energy systems, if a sustainable system is to be ensured in the long run, technological learning must be stimulated on a variety of innovative high efficiency and clean technologies. Substantial policy efforts are required concerning both RD&D efforts and measures to encourage the introduction and diffusion of new technologies and energy carriers into the marketplace. These policies should be formulated having in perspective the complex and dynamic forces that drive technological change.

2.2 The role of technology in climate change

At the global level, much attention has been focused in the climate change issue, because of the potentially serious consequences it may pose for the planet. Evidences of climate change have been mounting. Long-term records of the earth's global mean surface air temperature have shown a warming trend in the last century and the last decade has seen unusually warm years. Although a number of uncertainties about the processes involved still exist, the link between changes in concentration levels of greenhouse gases (GHG) in the atmosphere and climate change is established. Also, the anthropogenic emission contribution has been shown to be affecting the natural balance. Increasing concentrations of GHGs since pre-industrial times can be attributed to a large extent to human activities, mainly fossil fuel combustion, land use changes and agriculture. The Intergovernmental Panel on Climate Change (IPCC, 1995) already stated, "The balance of evidence suggests a discernible human influence on global climate".

CO₂ is one of the most important greenhouse gases. The combustion of fossil fuels in the global energy system is the main human-made source of CO₂ emissions to the atmosphere. CO₂ emissions from the energy system for the year 1990 are estimated in 6 Gt of Carbon. Such amount represented between 70% and 90% of total CO₂ emissions in that year (Nakicenovic et al., 1996b). Industrialised and economies-in-transition countries (grouped as the so-called Annex I countries) are currently the main energy consumers and CO₂ emitters but the developing world (non-Annex I countries) is expected to increase its contribution significantly in the future (Watson et al., 1996, IPCC, 2000).

Following the evidence gathered by the IPCC and the concerns about the consequences of climate change, the world community has discussed possible action, following the guidelines of the United Nations Framework Convention on Climate Change (UNFCCC - United Nations, 1992). The UNFCCC called for stabilisation of concentrations at a safe level (although such level still has to be determined) and outlined a range of principles to guide the corresponding decision-making. Among others, it appealed for the implementation of precautionary measures to minimise possible adverse effects, even in the absence of enough scientific certainty.

The result of the negotiations has been the Kyoto Protocol (United Nations, 1997), where Annex I countries have accepted commitments to achieve a reduction of their emissions, relative to 1990 levels, by the 2008-2012 horizon. The protocol, however, still has to be ratified by the parties.

The Kyoto agreement provides for some flexibility mechanisms to achieve the reductions. Among them are the possibility of trading emission permits, undertaking Joint Implementation projects among Annex I countries and the use of the Clean Development Mechanism (CDM). Emissions' trading allows countries to buy emissions permits from countries that have made reductions beyond their own needs. In the Joint Implementation scheme, countries may obtain credit toward their targets through project-based emission reductions in other countries. The CDM allows Annex I parties to profit from cheaper

mitigation options in non-Annex I countries, while helping the latter ones in achieving sustainable development.

One of the important points of such kind of agreements is how effective they are (or will be) in providing incentives for technological progress to reduce the world's energy intensity and for a transition towards non-fossil primary resources. For doing so, the implementation should take into account the relevant aspects of energy technology dynamics, as to encourage diversity of promising low-carbon highly efficient alternatives, stimulate their early technological learning with RD&D investments and deployment in niche markets and exploit "lock-in" processes in favour of emerging clean technologies (McDonald, 2000).

A number of studies have been devoted to examine the possible future trajectories of the global energy system and their impact on GHG emissions as well as the possibilities available for implementing emission reduction measures and the associated costs (for a review of existing emission scenarios see, for instance, Nakicenovic et al., 1998²⁶ or IPCC, 2000). The debate has been significantly influenced by the energy-economic models applied in the studies and their assumptions on, among other factors, technological change. The treatment given to technology in such models is one particularly relevant aspect affecting their results and the policy insights that can be gained out of them²⁷.

Ausubel (1995) already stressed the fact that the global warming debate underestimated the importance of technical change in reduction of emissions and adaptation to climate change. In his view, this could drive to an overestimation of the future Business-as-Usual emissions and, consequently, of abatement costs, when simple extrapolations of current technological systems are used in the projections. His main claim is that the recognition of the existence of technological trajectories and rates of progress will affect our perception of the cost structure of mitigation efforts.

One important aspect of the discussion concerns the optimal paths for the emissions. The debate about timing of abatement strategies was stimulated by the paper of Wigley et al. (1996), who claimed that, as the long term stabilisation of the atmospheric concentration of GHG appears to depend more on the emissions accumulated until the stabilisation time, rather than the emissions path followed²⁸, it could be economically meaningful to delay abatement actions until cheaper mitigation options become available and then undertake accelerated emissions reduction if necessary. In the mean time, efforts should be concentrated in R&D.

²⁶ On the basis of a comprehensive database, containing more than 400 scenarios, assembled by Morita and Lee (1998), Nakicenovic et al. (1998) have reviewed the range of emission projections available. They have found that, together with economic and methodological aspects, the assumptions concerning technological change play a key role in explaining the significant spread of emissions trajectories observed.

²⁷ For a review of the discussion see, for instance, Azar and Dowlatabadi (1999) or Grubb et al. (2000).

²⁸ Due to this fact the problem of stabilisation of atmospheric concentrations can be seen as one of allocating an approximately fixed allowable amount of emissions (the so-called carbon "budget") on time (Wigley et al. 1996). Therefore, in principle, an emissions trajectory may be followed, where higher short-term emissions are compensated by lower emissions on the long-term.

Several authors have criticised and responded this claim with arguments grounded on the nature of technological change. Rogner (1996a), noticing that up-front investments in new technologies and long periods of time are involved in the technological change process, observed that delay in taking action may lead to further lock the system into fossil fuels, hindering the reorientation of business strategies and diminishing the incentives to develop and adopt low carbon technologies. This would increase the risk of paying a much higher cost in the future if a faster, more abrupt, transition becomes necessary (provided the required rates of technological change could be achieved).

Grubb (1997) has observed that the interpretation of the fact that technology development can reduce the costs of abatement as an argument to defer emissions abatement is a consequence of conceiving technological change as an exogenous process. That is, occurring independently of market conditions, and, in this case, also of abatement efforts. In such view, in line with the so-called technology-push approach to understand technology, the process of accumulation of knowledge is thought to occur autonomously, driven by mainly R&D efforts.

Markets, however, play a key role in determining the evolution of technology. Technologies evolve in interaction with the markets they serve. Markets provide the ideal “playground” to accumulate experience and expectations of market opportunities influence the allocation of R&D efforts. The pressures posed by the market induce technology developments (demand pull factor). In fact, it must be recognised that both technology-push and demand-pull are important and interacting mechanisms of the technical progress process, although their relative importance could be different for each particular industry. Thus, the abatement strategies should include actions that regard the energy markets as instruments for technology development (Grubb, 1997), together with actions to foster the necessary R&D efforts.

Grübler and Messner (1998) have performed an analysis of optimal carbon paths using a coupled carbon cycle and energy systems model, examining the influence of treating technology dynamics as static, dynamic (exogenous) or endogenous (using learning curves). In such inter-temporal optimisation framework, alternative representations of technology dynamics and discount rates appear as very influential on emission paths. While confirming the emission patterns of Wigley et al. (1996), they arrive at different policy conclusions concerning the timing of abatement actions. In particular, they found that considering technological change as an endogenous process points towards immediate action to prepare the long-term departure from carbon intensive technologies. Action, however, does not necessarily means aggressive short-term abatement but efforts on R&D, demonstration projects and deployment in niche markets.

An additional influential factor relates to the high inertia displayed by the energy system. One of the aspects of such inertia has to do with the fact that the energy system is capital intensive and thus, the replacement of capital stock takes long periods. Thus, technology plays both the role of a change-enabling and inertial factor in the energy sector. This fact has also been used as an argument for delaying abatement.

Of course, premature retirement of technology already in place will be very costly. The capital turnover, however, is a continuous process and if actions to introduce less-intensive carbon technologies were delayed, there would be a higher risk of incurring in higher costs if a faster transition is required in the future because costly carbon-intensive investments would have to be prematurely discarded. Even more, the deployment of additional carbon-intensive infrastructure during the delaying period could make more difficult to achieve the necessary reduction targets in the future.

Thus, it is important to make use of the opportunities provided by the continuous natural replacement of obsolete capital stock to introduce more efficient and less polluting technologies, also, taking into account that slow stock turnover rates will be a conditioning factor of the speed at which penetration of such technologies may take place (Grubb, 1997).

Nakicenovic (1997) stresses that the further decarbonisation requires the emergence, across the economy, of a whole new cluster of innovative technologies, which will enable to increase efficiency and cleanliness of the energy system. As already mentioned, in his work it has been emphasised that technological change is a cumulative learning process, where actual deployment of technologies in the markets accounts for a significant part of the learning and improvement that render a technology competitive. Without the possibility to generate and accumulate technological knowledge, it will not be possible to prepare the cluster of innovative technologies necessary for the long run transition away from a carbon intensive energy sector. And, given the long time constants of technological change in the energy systems, such accumulation of experience must start early. Early learning is a necessary precondition for the successful promotion of such new cluster of technologies.

The discussion about GHG mitigation strategies is a very complex one with many different elements playing a role. Scientific, technical and economical aspects but, even more, social and political ones intervene and uncertainties abound. Technology dynamics, however, must be recognised as one of the essential factors in the climate change debate and its implications must be carefully examined in order to incorporate them into the corresponding policy-making process.

Although one should be careful in not interpreting arguments based on the dynamics of technological change as a direct call for immediate strong GHG abatement, the understanding of technological change as an endogenous, cumulative and self-reinforcing process points in the direction of early, diversified and gradual actions to influence the long-term evolution of the energy systems and prepare for possible contingencies (Grübler and Messner, 1998).

Such early actions mean that opportunities have to be provided for the insertion of a diversified portfolio of new technologies. Only a continuous effort on R&D and demonstration projects together with the creation and support of niche markets will allow the accumulation and self-reinforcing of learning and experience necessary for cost and performance improvements of the new technologies, which will enable them to reach full competitiveness in energy markets, and therefore to contribute to a sustained long run decarbonisation path (Kemp, 1997a).

2.3 Evolution of some energy technologies

In this numeral, a brief description is presented of the development of some emerging energy technologies that may play a significant role in the transition to more efficient, less carbon-intensive energy systems. Where possible and information is available, their learning characteristics are described. Attention is concentrated on six electricity generation technologies: The gas turbine, solar photo-voltaics, wind turbine, fuel cells, clean coal technologies and advanced nuclear power plants. Such technologies are incorporated in the model analyses performed below.

2.3.1 Wind turbines

Wind turbines are an emerging renewable electricity generation alternative that has experienced a highly dynamic growth in the last years. Growth rates have been around 20%/year in the last ten years and installed capacity reached 13.4 GW by the end of the year 1999. In response to market-stimulation incentives and government support in several countries, wind turbines have been able to penetrate to a certain extent the global marketplace. However, in several cases the installation of wind capacity that took place as a response to the incentives declined once such measures began to be dismantled (Loiter and Norberg-Bohm, 1999). The market was not able to acquire its own growth dynamics. Also, in some instances, incentives appear to have been concentrated on investment on capacity, rather than actual production of electricity, thus resulting in unused or sub-optimally operated facilities.

The development of wind turbines can be seen as a process of incremental improvements based on experience in production and use (Neij, 1999a). The most successful approach, followed, for instance, by Denmark, currently one of the major players in the world market, was the scaling up of small windmills. Incremental innovations were gradually incorporated to standard designs, allowing the production of successive models with increased size, improved performance and lower costs (Loiter and Norberg-Bohm, 1999). Other countries that followed a different approach, starting with MW-size turbines and emphasising R&D expenditures rather than deployment, such as Sweden and Germany and also some programs in the U.S. were not successful.

As a rule, experience gained with deployment of capacity seems to have been critical for progress in wind turbines, having also an influence in the effectiveness of R&D efforts. R&D programs seem to have been more successful when addressing specific problems made evident by the operation experience (Loiter and Norberg-Bohm, 1999). Having a market where new R&D results could be tested was an important feedback mechanism for research and focusing on concrete challenges allowed a more agile and wide incorporation of the innovations produced in such programs in subsequent generations of the technology.

Larger turbines with improved performance, together with higher towers and better estimation of resources, have contributed to increase wind capture. Future efforts should be devoted to further increase wind capture, reduce mechanical stresses and noise and further

decrease costs. Developments to reach those goals may include further up-scaling, new types of generators, variable speed operation, new manufacturing methods and increased flexibility of the turbines by means of advanced blades (new materials, control systems and different configurations).

Wind turbines have experienced significant cost reductions. Christiansson (1995) reported a progress ratio of 84% for turbines built in the U.S. for the period 1981-1987. ISET(2000) estimates a progress ratio of 93% using prices for the German market during the period 1990-1999. Neij (1999a) presents a detailed analysis of learning within the Danish wind industry, reporting a progress ratio of 92% for all Danish wind turbines in the period 1982-1997²⁹. According to her analysis, costs reductions have been mainly due to up scaling of turbines. Reductions may have been limited by costs added due to design changes and the fact that the rapid introduction of new models did not allow to fully benefit from the effects of mass production. Also, many components were originally used in other applications and, therefore, they could have experienced cost reductions previously. Thus, the learning process has been relatively slow, although the compounded result has been considerable. Although no significant breakthroughs are expected for this technology, interesting capital and O&M cost reductions and incremental performance improvements can still be expected which, consequently, will drive to lower electricity generation costs (Neij, 1999a).

The wind turbine is already attractive in some markets, but it still has to consolidate itself as a competitive alternative. In order to achieve that, there are a number of concerns regarding reliability, land use, visual impacts, wind resource information, etc., that must be addressed. Also, technology policy instruments may be required to provide specific incentives to the production of electricity (and not only capacity installations) from this and other new technologies (Loiter and Norberg-Bohm, 1999).

2.3.2 Solar photo-voltaics

Solar photo-voltaics (PV) has undergone significant improvements, constituting already a sound option for off-grid remote and special applications (Thomas et al., 1999). In the last fifteen years, the technology has been growing at an average of 16%/year having reached 941 MW of cumulative shipments in 1998. The rapidly growing business has recently received the interest of several big companies and research activities have been intensified (Sweet, 1999). It still depends to a large extent on niche markets but these have been expanding as cost reductions have manifested.

Several analyses of the learning curve for PV modules have reported historical values for the progress ratio around 80%. Christiansson (1995), reporting some estimates from the

²⁹ Such figure is, however, for the aggregate of all turbine classes and manufacturers. The same analysis also found variability on the progress ratio, according to the grouping made for the estimation. For instance, when considering only turbines from dominant manufacturers with long-term experience, the progress ratio was 94%. Also, if a single type (size) of turbines was examined, progress ratios were close to 100%, which reveals the changing configuration of the technology along the learning and diffusion processes. The example illustrates the fact that progress ratio estimates are very dependant on the underlying data. Different time spans, technology categories as well as use of cost or prices will be influential in the result.

literature, shows a progress ratio of 82% for PV cells in the US for the period 1976-1992 and 81% in Japan from 1979 to 1988. Cody and Tiedje (1997) estimate a value of 78% for the period 1976-1988. The most recent estimation seems to be that of Harmon (2000), who assembled data for the world market between 1968 and 1998, finding a progress ratio of 79.8%.

Learning curve estimations have mainly been applied to the cost of PV modules, since the quantification of trends for the Balance-of Plant (BOP) appears more difficult due to the lack of continuous data and big differences from one case to the other. However, BOP costs have also experienced significant decreases and such reductions constitute an essential factor in the learning of the technology. Thomas et al. (1999), for instance, compared costs for a grid-tied PV system in the U.S. in 1980 with those of a similar system in 1998 and found that BOP cost reductions may have been even faster than those of PV modules.

Although appreciable cost reductions have occurred in the last decades, the technology is still in the early part of its learning curve and it is currently too expensive for utility grid applications. Nonetheless, there is ample room for efficiency and cost improvements (Cody and Tiedje, 1997).

Watanabe (1995, 1999) has studied the existence of the so-called "virtuous cycle" for solar photo-voltaics in Japan. On the basis of an analysis of the role of public and private R&D expenses and industrial production in the competitiveness of the technology, he identified a positive feedback loop between R&D, market growth and price reduction which stimulated its development. It is expected that such cycle of cost reductions driving to bigger market shares which, in their turn, drive to further cost reductions, will continue in the future.

Besides the already more or less well established niche markets, a very promising sector is the application of PV systems to buildings. Existing building structures can be used to mount the PV system or this one can be integrated within the building. Grid-connected building PV systems could bring the larger scale deployment required to foster the technology and if they do so, they will constitute a bridge for its long-term penetration in the bulk electricity markets (Oliver and Jackson, 1999).

However, in order to ensure a sustained growth of current markets and the entrance to broader ones, a number of factors must be taken into account. Of course, major cost cuts and efficiency improvements are still necessary to enable competitiveness. Thus, development of materials, which allow lower cost manufacturing with higher conversion efficiency is a critical success factor (Benner and Kazmerski, 1999).

Also, as availability of raw materials such as glass may become an issue for large scale production, PV technologies using less amounts of cheaper materials may be favoured (Shah et al., 1999). In addition, reductions must be achieved not only in the module costs but also in the Balance of Plant, particularly in area-related costs. In such perspective, although the current market is still dominated by the standard crystalline silicon cells, thin-film cells, enabling to reduce material costs and collecting area, provide an attractive alternative and are expected to play an increasing role in the future PV market.

Besides technical aspects other issues are also relevant for the future competitiveness. Among them, the standardisation of components, materials and designs, which will allow to profit from production scale effects, and will ease the inputs supply for the PV industry and the installation of the technology to the final user should be addressed (Benner and Kazmerski, 1999). Also, new business strategies, emphasising the sales of complete service solutions, instead of a technology, and alliances between manufacturers must be explored and an adequate infrastructure for finance, distribution, installation and support developed.

The importance of developing new strategies to stimulate the interest of potential adopters in solar photo-voltaics is well recognised. Kaplan (1999), for instance, has stressed the need to consider specific schemes for groups beyond the so-called early adopters, arguing that the decision-making process of early and later potential adopters are different and thus require different stimuli. While early adopters, being more risk-taking, may rely on available technical and economical information to make a decision, for other groups of adopters the sole availability of such technical knowledge may not be sufficient to make a favourable decision. Thus, an approach based on allowing them to become "familiar" with the technology by promoting trial and error and learning through experience, for instance with small experimental projects, could be more effective than a conventional commercialisation process.

2.3.3 Gas fuel cells

The fuel cell is a technology mainly in the demonstration phase, but very promising for both transportation and stationary power applications. It allows the direct conversion of the chemical energy in the fuels to electricity (without combustion), thus being able to reach high efficiencies and significantly low polluting emissions. Hydrogen, the internal fuel of the cell, is produced out of other fuels. Electricity is produced by oxidising hydrogen. There is a great diversity of fuel sources from which the hydrogen necessary for the operation may be produced. Among others, natural gas, methanol, ethanol, petroleum distillates, biomass and even gasified coal can be used (Lloyd, 1999).

There are different types of fuel cell depending basically of the electrolyte being used: Alkaline, Proton Exchange Membrane (PEM), Phosphoric Acid (PAFC), Molten Carbonate (MCFC) and Solid Oxide (SOFC) fuel cells (Gregory and Rogner, 1998).

The phosphoric acid one, operating at approximately 200 °C, is currently the more mature. Small units of PAFC, up to 200 kW, are being commercially available since the beginning on the 90's, and have been applied mainly for on-site co-generation (DOE/FE, 1996). Although also some MW-size units have been tested, some developers seem willing to favour small size units (up to 500 kW) for distributed stationary applications such as powering commercial buildings or even individual homes (Lloyd, 1999). Such trend could open interesting possibilities for the future configurations of electricity supply systems.

Distributed systems, in contrast to the today's centralised ones, could emerge, driving to a reorganisation of energy markets.

Solid oxide fuel cells (SOFC) operate at high temperatures (between 800 and 1000 °C). This provides the possibility of internally reforming fuels to produce the hydrogen and makes them attractive for cogeneration of heat and electricity, although imposes stringent requirements in the material specifications. They can also be applied in hybrid systems combining a fuel cell and a gas combined cycle turbine.

The PEM cells, operating at lower temperatures (around 80 °C), and offering high conversion efficiency and fast transient response as well as some advantages in the manufacturing process, are receiving a lot of attention for mobile applications (Gilchrist, 1998). Fuel cells producers and automobile manufacturers are co-operating in several joint venture programs to develop fuel cell-powered vehicles. Small demonstration bus fleets are already operating and different passenger car concepts have been tested. PEM fuel cells have experienced a series of advancements in weight, power and cost in the last years, which have reduced their distance to commercial viability and make them a possible important competitor for the internal combustion engine in the future. However, issues related to the systems to convert other fuels into hydrogen (on-board reforming or external conversion) and the deployment of the corresponding fuel production, storage and distribution infrastructures must be addressed (Thomas et al., 2000).

Although a significant potential for cost reductions exist, there is uncertainty about future cost levels. A wide range of future cost projections exists in the literature³⁰. Being the technology still in the R&D phase, little information about learning curves is available. Whitaker (1998), on the basis of data from a commercial manufacturer of stationary fuel cell power plants, claims a PR of 75% is possible. Thomas et al. (1998) conducted analyses for penetration of fuel cell vehicles using an estimated PR of 82%. Low-cost conductive materials must be introduced, specifically tailored system components developed and the lifetime must be extended in order to cut costs. Also, manufacturing costs will be reduced if high-volume production methods can be applied. Such economies of volume become particularly relevant for the stationary power market now that emphasis seems to have changed toward smaller unit sizes. At this stage the technology may critically depend on the creation of market volume in order to stimulate a "virtuous-cycle" that will enable further cost reductions and thus accelerate market penetration.

The fuel cell has still a long way to go to become cost-competitive, but in several stationary power applications it is beginning to be chosen due to its comparative cleanliness, high efficiency, silent operation, modularity, multiple fuel choice and grid independence. It can conquer and expand niche markets if further performance and cost improvements can be achieved. Possible niche markets for stationary power generation are supply of loads with stringent reliability requirements, facilities where waste methane gas is available such as land fills, portable power sources such as emergency power devices or outdoors equipment

³⁰ See, for instance, Padró and Putsche (1999) for a review of costs reported in the literature.

as well as particular cogeneration applications. However, it is expected that transportation applications will lead the penetration of the markets.

2.3.4 Clean coal technologies

Clean coal technologies, such as pressurised fluidised bed combustion (PFBC), atmospheric fluidised bed combustion (AFBC), and integrated gasification combined cycle (IGCC) allow a more efficient and less polluting generation of electricity than conventional pulverised coal-fired plants. They have already experienced significant advances and expectations about their future cost reductions have been positively changing in the last few years (Schrattenholzer, 1998a).

Fluidised-bed combustion systems are one of the most mature clean coal technologies. Some commercial plants are already in operation or construction. In such systems, jets of air suspend the burning coal over a bed of inert material, providing improved combustion conditions (DOE, 2000). With the addition of a sorbent to the bed, sulphur released in the combustion can be captured. PFBC systems, where the process occurs in a pressurised environment, allow operation also in a combined cycle mode. As combustion takes place at elevated pressures and temperatures, a high-pressure stream is produced that can drive a gas turbine, while the steam generated may be applied to a steam turbine (DOE, 2000). Fluidised-bed systems exhibit high fuel flexibility. They can operate with different types of coal, biomass or even low-grade fuels such as petroleum coke.

IGCC is the cleanest and more efficient coal-fired power generation alternative available. In IGCC systems, coal is gasified and the resulting gas is cleaned prior to combustion in a combined cycle gas turbine. Such process facilitates removal of the coal's sulphur and particulate and reduction of nitrogen oxide emissions (DOE, 2000). Although less flexible than PFBC, other fuels such as biomass or heavy liquid fuels could also be utilised. A few IGCC plants are already in demonstration in several countries.

However, the technology is still very expensive to be competitive. One alternative to make it attractive is the co-production of electricity and syngas-derived products (DOE/FE, 1998). The use of disadvantaged low-cost fuels such as heavy petroleum liquids or petroleum coke may also contribute to cost savings. On the other hand, taking advantage of its modular nature, the technology could be applied for retrofitting of existing plants.

Although their market perspectives could be affected by CO₂ reduction policies, clean coal technologies would be an interesting alternative for those countries, which, due to resource constraints, will still have to rely on coal to meet fast growing electricity consumption. However, although their higher environmental compatibility may act as an incentive for adoption, cost reductions are necessary if they are to achieve a significant market share. Also, they still require further technical improvements. Further efficiency increases, more fuel flexibility and design simplifications that allow higher reliability seem to be possible. In addition, their technical and commercial viability must be proven with more demonstration projects. Schemes to support demonstration plants that provide incentives

for sharing commercial risks between manufacturers, power utilities and governments must be conceived.

Some evidence of learning has been found for the construction costs of conventional coal power plants, when leaving aside the costs incurred as response to environmental regulations (Joskow and Rose, 1985). However, besides the analysis of MacGregor et al. (1991), which found a progress ratio of 83.6% for the early phase of development of the IGCC power plant, no additional learning curve analyses appear to be available for clean coal technologies in the literature. This may be due, among other factors, to the uncertainty in installed capacities as the technologies are still in an early stage of deployment. However, analyses have been reported with a moderate PR of 94% for a generic advanced coal technology (Messner, 1997).

2.3.5 Gas turbines

The gas turbine has become one of the most competitive alternatives for electricity generation and cogeneration due to its low investment costs, short construction times, high efficiency, low emissions and modularity. It is expected to rapidly increase its share in the electricity market.

In single cycle systems, high temperature, high-pressure gas is used to drive a combustion turbine. In a combined cycle configuration, the waste heat from the combustion turbine is used to generate steam for an additional steam turbine stage. The technology can be considered as approaching maturity but incremental improvements in efficiency, costs and emission levels can still be expected. Further efficiency improvements will depend strongly on the development of new high-temperature materials, advanced cooling techniques and a better use of the gas turbine exhaust (Batista, 1996). Another important factor relates to the possibility of using several fuels. With the current status, the technology already exhibits some limited fuel flexibility. It is expected that future advanced turbines may expand such flexibility to use coal-derived synthesis gas and biomass-based gas.

The technology initially emerged as an engine for aircraft (turbojet) propulsion. Afterwards, it was adapted for electricity generation. Being competitive in meeting peak loads and for reliability enhancing purposes, it found niche applications in generation markets. The existence of a global electricity market multiplied the opportunities for learning-by-doing and learning-by-using processes in the gas turbines business. Also, the technology benefited from a series of developments in aerodynamics, materials, manufacturing and quality control methods, etc. The resulting continuous performance and cost improvements, combined with the slowing down of progress in conventional steam turbines, the launch of institutional restructuring and privatisation processes in the electricity sectors of many countries and increasing environmental concerns, paved the way for its introduction as a competitor into base-load electricity generation and following successful penetration of the market (Islas, 1999).

Gas turbines have experienced significant cost reductions along their history. Interestingly, the learning curve has changed in successive stages of their life cycle. MacGregor (1991)

presented a learning curve of simple cycle gas turbines using data for the period 1958-1980³¹. The technology exhibited a rapid learning (PR=80%) in the R&D and demonstration phase (1958-1963), but learning slowed down (PR=90%) once it went to the commercialisation phase (1963-1980). In this second stage, as niche markets expanded, the technology "became increasingly competitive through continued improvements that were sustained by substantial investments" (Grübler et al., 1999).

Claeson (1999) carried out another analysis. The learning curve of the combined cycle gas turbine was examined using investment prices (not costs) from 1983 to 1997. According to such analysis, the technology actually experienced price increases with accumulation of experience (i.e. PR > 100%) during the period 1983-1990 and experienced again decreases in the period 1991-1997 (PR=75%), probably due to increasing competition among manufacturers to gain market share (market "shake-out" phase). Although a cost trend is difficult to establish, out of price trends³², Claeson (1999) estimates that a likely future progress ratio for investment costs could be around 90% once the market stabilises. In the analyses carried out here learning has been considered for the combined cycle gas turbine.

2.3.6 New nuclear power plants

The nuclear fission option is not new. It was introduced about fifty years ago and currently has a market share of approximately 17% of the world's electricity market. But, after having experienced a significant growth in the past decades, nuclear capacity expansion has become much slower. In several countries the nuclear power industry faces moratoria for new capacity additions or even plans for decommissioning of existing plants. Other countries, however, such as Japan, South Korea and France continue to support nuclear power. Asian countries, in particular, are expected to play an important role in the future markets for nuclear energy (PCAST, 1997).

Construction and operation costs of nuclear facilities have shown an increasing trend due, among other factors, to the imposition of more stringent and much more voluminous regulatory requirements and longer building times. Such long construction periods and the higher capital investments of a nuclear central also make it less attractive in current liberalised electricity markets. Reduction of construction times, standardisation of components and simplification of designs, control of operating costs and the examination of impacts of possible excessive regulation in costs will be essential to improve the cost effectiveness of the technology (PCAST, 1997).

On the other hand, there is still no definitive solution for the radioactive waste problem. Many countries contemplate the use of geological repositories for permanent disposal. Thus, the future of nuclear power appears uncertain and the issues of guaranteeing safety, improving public confidence, disposal of spent fuel and possible risks of proliferation of nuclear weapons still have to be solved. Continuous R&D efforts on these aspects will be

³¹ This case study is discussed also in IIASA-WEC (1995).

³² As it is known, prices may be subjected to fluctuations due to market instability or corporative strategy of the firms involved, which may mask underlying cost trends.

essential to reduce the obstacles that impede the technology to play a significant role in the global energy portfolio.

Addressing successfully such issues is likely to require a new generation of nuclear plants. New designs of nuclear power plants are emerging, which are expected to be safer and less costly. Inherently safe designs applying passive safety principles are being explored. Some efforts are also being devoted to the development of smaller reactors, which could be more easily accommodated to the needs of developing countries (Gregory and Rogner, 1998). Such developments, if successful, could contribute to break the current stagnation trend. In addition, the nuclear option could be attractive if significant CO₂ emission reductions must be achieved. Still, the technology has to improve its cost-competitiveness and the industry has to strengthen the nuclear safety regime and promote greater public acceptance (ElBaradei, 2000).

Although there is evidence of cost reduction due to learning effects in the very early stages of introduction of nuclear power units (Zimmermann, 1982), conventional nuclear power plants have not shown capital cost reductions as a result of cumulative experience, among other factors due to ever-increasing safety regulations. Learning effects may have manifested in other performance indicators such as increased safety and reliability of operation. Nonetheless, new technologies could exhibit a different dynamics. First-of-a-kind units of the newly designed plants would certainly be expensive, but there are expectations that experience with them may lower construction and operation costs (EIA, 1998). Here, a conservative progress ratio of 96% is considered for a generic advanced nuclear power plant.

3. Endogenising learning curves in optimization models

In this chapter, the methodological approach used here to endogenise the experience curves in the linear programming models is described. Relevant variables and parameters are defined and the corresponding equations are presented.

The endogenisation of learning curves in energy optimisation models drives to some mathematical difficulties. The non-linear formulation (NLP) of the learning curves is, due to the presence of the increasing returns mechanism, a non-convex optimisation problem. Such kind of problems possesses several local optima, and a global optimal solution cannot be guaranteed with the normal non-linear optimisation solvers³³. Using Mixed Integer Programming (MIP) techniques, a linearisation of this non-linear, non-convex program can be achieved. Such approach consists of a piece-wise approximation of the total cumulative cost curve, using integer variables to control the sequence of segments along the curve. Although more computer intensive, it enables to find a global optimum.

Endogenisation of experience curves in energy system optimisation models using the MIP approach have been reported by Messner (1995, 1997) for the MESSAGE model³⁴ and Mattsson(1997) for the GENIE model³⁵. In this section, the NLP and MIP formulations of the learning curves used in the ERIS (Kypreos and Barreto, 1998a) and MARKAL (Kypreos and Barreto, 1998b) models are described. For the MIP approach two different alternatives are presented. The first one corresponds to the one described by Mattsson (1997) and was used for the applications reported here. The second one, based on the one presented by Messner (1997), is only briefly described. The implementation of this second procedure resulted in very similar solution times to the first one.

The code to incorporate experience curves using the MIP approach in the MARKAL model is presented in Appendix 1.

3.1 Definition of cumulative capacity

The cumulative capacity of a given technology k in the period t corresponds to the summation of the investments (in physical units) up to time t , plus the initial cumulative

³³ This behaviour is however interesting to the policy analyst, as it illustrates how, under the presence of increasing returns, a system may evolve in significantly different directions. Analyses by Mattsson and Wene (1997), with the non-linear non-convex version of the GENIE model, illustrate that different local optimal solutions may be reached, which exhibit a very different technology dynamics but a very similar cost. Such local minima are of interest because they represent situations where the system has followed a trajectory that drives to its "lock-in" to a certain technology or group of technologies.

³⁴ MESSAGE is the energy optimisation model developed and applied at the International Institute for Applied System Analyses (Messner and Strubegger, 1995).

³⁵ GENIE is the Global Energy System with Internalized Experience Curves Model (Mattsson, 1997).

capacity that defines the starting point on the experience curve ($C_{k,0}$). The cumulative capacity ($C_{k,t}$), a non-decreasing variable, can be expressed as³⁶:

$$C_{k,t} = C_{k,0} + \sum_{\tau=1}^t INV_{k,\tau} \quad (5)$$

$k \in \{1, \dots, K\}$, $t \in \{1, \dots, T\}$

With:

$C_{k,0}$: Initial cumulative capacity (parameter)

$INV_{k,t}$: Investments made on this technology in a particular period t (variable).

3.2 Definition of the cumulative cost curve

The functional form of learning curves described above in chapter 1 is not used directly when endogenising them in perfect foresight optimisation models, because it would lead to a severe non-linearity in the objective function of the problem. The concept of cumulative cost is used instead. The total cumulative cost ($TC_{k,t}$) is expressed as the integral of the specific cost curve (see Figure 4):

$$TC_{k,t} = \int_0^C SC_{k,t}(C) * dC = \int_0^C aC_{k,t}^{-b} * dC = \frac{a}{1-b} C_{k,t}^{1-b} \quad (6)$$

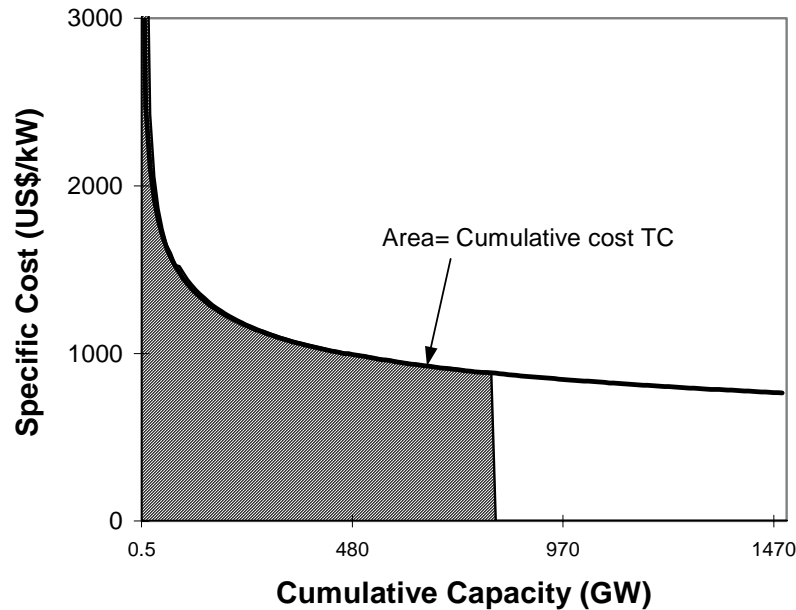


Figure 4. Cumulative cost curve as the area below the learning curve

³⁶ In ERIIS the cumulative capacity $C_{te,t}$ is not used directly as a variable, but the equivalent product $G_t^{te} * dcap^{te}$ is used instead. $dcap^{te}$ is the initial cumulative capacity (denoted as $C_{k,0}$ in the text) of a given technology t and G_t^{te} is the relative growth factor (a variable) respect to $dcap^{te}$. However, reference to $C_{te,t}$ is made here for explanatory purposes.

3.3 Definition of the investment cost

The investment cost $IC_{k,t}$ associated to the investments in a given learning technology k in the period t is computed as the subtraction of two consecutive values of the cumulative cost:

$$IC_{k,t} = TC_{k,t} - TC_{k,t-1} \quad (7)$$

These investment costs are discounted and included in the objective function.

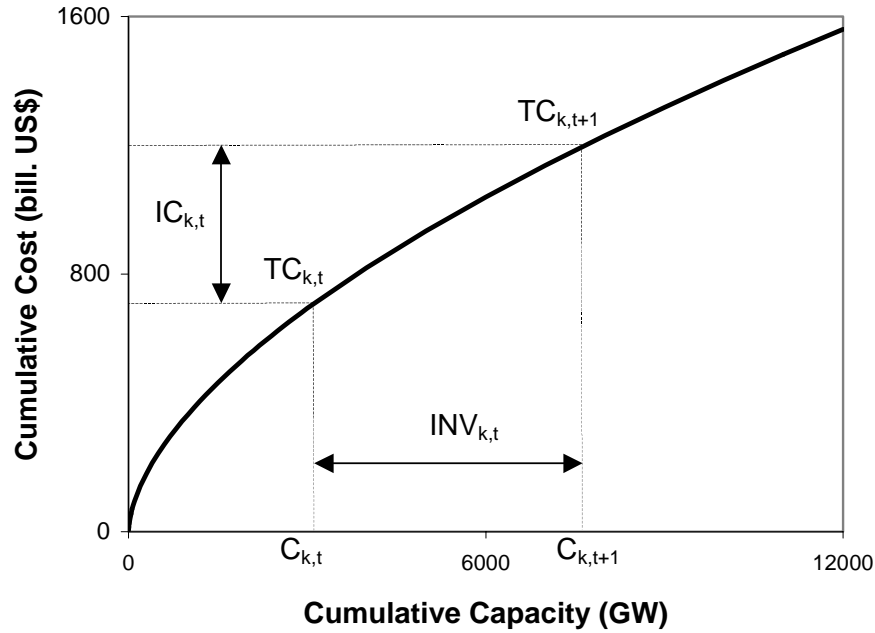


Figure 5. *Investment costs computed with the cumulative cost curve.*

In the NLP formulation the equation (6) presented above is replaced directly in equation (7) to compute the investment costs per period for a given technology. That is:

$$IC_{k,t} = \frac{a(C_{k,t}^{1-b} - C_{k,t-1}^{1-b})}{1-b} \quad (8)$$

Such investment costs are discounted and directly incorporated in the objective function³⁷. Thus, the problem becomes a program with a non-linear, non-convex objective function but linear constraints.

The MIP procedure, on the other hand, provides a piece-wise representation of cumulative cost curve (the curve is approximated by a set of contiguous straight lines, see Figure 6 below) and the corresponding $IC_{k,t}$ term is computed using equation (7) as a constraint of the model.

³⁷ See Appendix 2 for the LP, NLP and MIP objective functions of the ERIS model.

The new objective function (Z') comprises the usual computation of all the costs for the other non-learning technologies (Z), plus the discounted investment costs for the k learning technologies:

$$Z' = Z + \sum_k \sum_t df_t * IC_{k,t} \quad (9)$$

Where df_t : Discount factors.

In the remainder of this chapter the MIP approach is described in more detail.

3.4 Maximum cumulative capacity and cumulative cost

In order to specify the curve to be interpolated, a maximum cumulative capacity $C_{k,max}$ must be defined. $C_{k,max}$ implies an upper bound for the capacity of the technology and will affect the segmentation as discussed below in numeral 4.2.3.3. The corresponding maximum cumulative cost is given by:

$$TC_{k,max} = \frac{a}{1-b} (C_{k,max})^{1-b} \quad (10)$$

3.5 Declaration of number of segments

The number of segments N for the cumulative cost curve must be specified. N determines the number of integer variables per technology and period. Its choice is a trade-off between the precision required for the approximation and the solution time.

3.6 Definition of the kink points for cumulative costs and capacities

Using the initial and final points of the curve and according to the number of segments previously defined, the breakpoints are computed. Taking into account that a faster decrease of costs occurs in the first region of the curve, in this particular formulation a segmentation procedure with variable length segments, shorter ones at the beginning and then increasingly longer segments, is used in order to obtain a better representation for the first region of the curve. The segments are defined as follows:

For $i=0, \dots, N-1$

$$TC_{i,k} = TC_{0,k} + \frac{1}{2^{N-i}} \frac{(TC_{k,max} - TC_{0,k})}{\sum_{i=0}^{N-1} \frac{1}{2^{N-i}}} \quad (11)$$

And the corresponding cumulative capacities:

$$C_{i,k} = \left(\frac{(1-b)}{a} (TC_{i,k}) \right)^{\frac{1}{1-b}} \quad (12)$$

An example of this type of segmentation is shown in Figure 6. Although it is relatively insensitive to the variations of the $C_{k,max}$ and the number of segments, it is a good compromise and gives adequate and stable results. For a discussion of the influence of the segmentation procedure, see numeral 4.2.2.1 below.

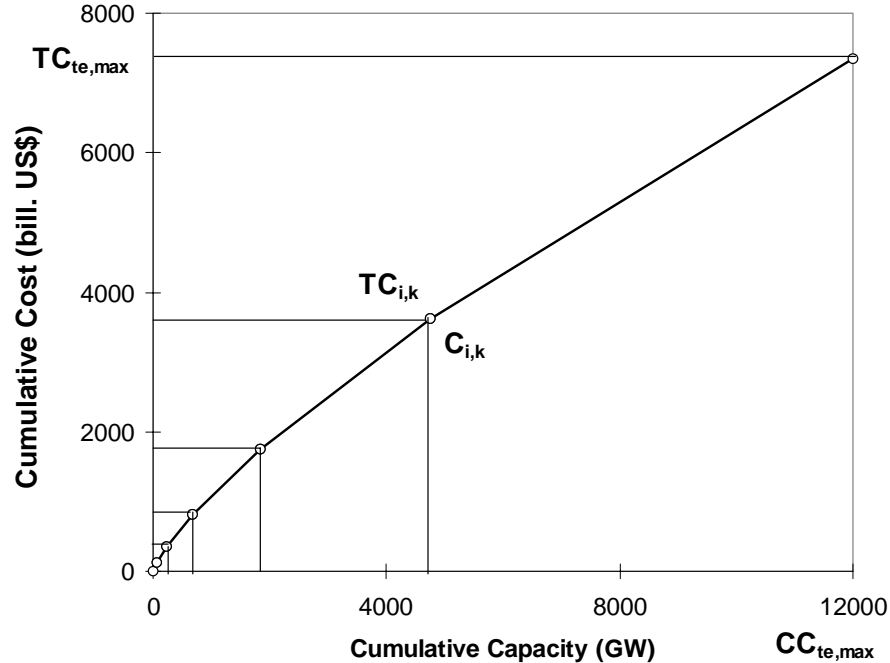


Figure 6. Piece-wise approximation of the cumulative cost curve

3.7 The first interpolation procedure

The basic idea of the MIP approach relies upon a procedure to interpolate a piece-wise linear function $f(x)$ composed of $N-1$ line segments connected by N knot points (Sierksma, 1996). This procedure uses binary variables to express points on the piece-wise curve as convex combinations of adjacent knots in the curve allowing the description of the stepwise function as an equivalent of several linear constraints that can be handled by a MIP model. The basic formulation of the interpolation is as follows:

- Interpolation of cumulative capacity

The cumulative capacity is expressed as a summation of continuous lambda variables. There will be as many lambda variables as segments have been defined:

$$C_{k,t} = \sum_{i=1}^N \lambda_{k,i,t} \quad (13)$$

- Interpolation of cumulative cost

The cumulative cost is expressed as a linear combination of segments expressed in terms of the continuous lambda and binary delta variables:

$$TC_{k,t} = \sum_{i=1}^N \alpha_{i,k} * \delta_{k,i,t} + \beta_{i,k} * \lambda_{k,i,t} \quad (14)$$

$$\delta_{k,i,t} \in \{0,1\}$$

Only one delta variable will be non-zero at the same time, indicating the active linear segment. The coefficient $\beta_{i,k}$ represents the slope of each one of the segments.

$$\beta_{i,k} = \frac{TC_{i,k} - TC_{i-1,k}}{C_{i,k} - C_{i-1,k}} \quad (15)$$

The coefficient $\alpha_{i,k}$ is the corresponding TC-axis intercept of each linear segment.

$$\alpha_{i,k} = TC_{i-1,k} - \beta_{i,k} C_{i-1,k} \quad (16)$$

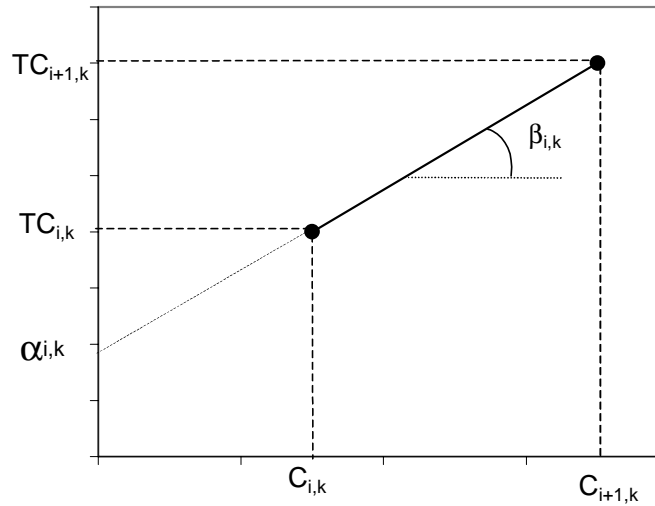


Figure 7. *Cumulative cost curve segmentation. Detail.*

Although the piece-wise representation is made directly on the cumulative cost curve, the examination of the resulting stepwise curve for the specific cost provides an idea of its accuracy. The equivalent specific cost (SC) for each segment corresponds to the coefficient $\beta_{i,k}$. Figure 8 presents the specific cost curve corresponding to the variable length segmentation described above. As mentioned, the parameters $C_{k,max}$ and N as well as the segmentation procedure affect the resulting piece-wise approximation of the non-linear learning curve and have to be defined carefully. For a discussion of their influence see numeral 4.2.2 below.

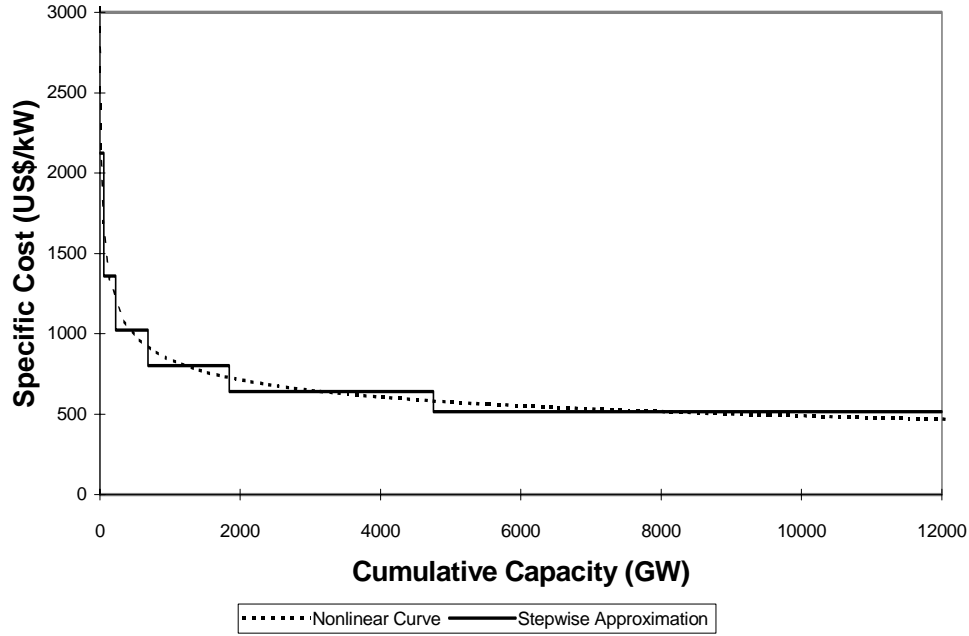


Figure 8. *Stepwise approximation of the specific cost curve. Variable length segments.*

- Logical constraints

The logical conditions that control the active segment of the cumulative cost curve are defined using the help of the binary variables delta:

$$\begin{aligned} \lambda_{k,i,t} &\geq C_{i,k} * \delta_{k,i,t} \\ \lambda_{k,i,t} &\leq C_{i+1,k} * \delta_{k,i,t} \end{aligned} \quad (17)$$

This group of constraints basically relates the continuous variable $\lambda_{k,i,t}$ to a corresponding binary variable $\delta_{k,i,t}$, ensuring that lambda remains between the two corresponding successive cumulative capacity points ($C_{i,k}$ and $C_{i+1,k}$).

- Sum of delta variables to one

In order to ensure that only one binary variable is active each period, for every technology k and every time period t , the sum of delta binary variables is forced to one:

$$\sum_{i=1}^N \delta_{k,i,t} = 1 \quad (18)$$

- Additional constraints

Using the fact that experience must grow or at least remain at the same level, additional constraints can be added to the basic formulation. They restrict the $\delta_{k,i,t}$ variables that can be

chosen in a given period, thus helping to reduce the solution time. The basic rationale behind such constraints is the fact that in the period $t+1$ the technology will either remain on the segment of the curve where it was located in the period t or move to a further one, but cannot go back to a previous one. Thus, these constraints provide a relation between the binary indicator variables $\delta_{k,i,t}$ across periods, according to the sequence that must be followed:

For $t=1, \dots, T, k=1, \dots, K, i=1, \dots, N$

$$\begin{aligned} \sum_{P=1}^i \delta_{k,P,t} &\geq \sum_{P=1}^i \delta_{k,P,t+1} \\ \sum_{P=i}^N \delta_{k,P,t} &\leq \sum_{P=i}^N \delta_{k,P,t+1} \end{aligned} \quad (19)$$

3.8 The second interpolation procedure

This formulation differs from the first one only in the interpolation of the cumulative capacity and cost and the definition of the corresponding logical constraints. An additional constraint regarding the summation of lambda variables, which have now a different definition, is also added. Only the expressions where a change is due are described. The others remain as described for the first one.

- Interpolation of cumulative capacity

The cumulative capacity is expressed as a weighted summation of the breakpoints, where the weighting factors are the lambda variables. The number of lambda variables will correspond to the number of breakpoints specified ($N+1$ points if N segments are specified).

$$C_{k,t} = \sum_{i=0}^N \lambda_{k,i,t} * C_{i,k} \quad (20)$$

- Interpolation of cumulative cost

The cumulative cost is also expressed in terms of the corresponding breakpoints weighted by the lambda variables.

$$TC_{k,t} = \sum_{i=0}^N \lambda_{k,i,t} * TC_{i,k} \quad (21)$$

- Sum of lambda variables to one

For every technology k and every time period t , force the sum of lambda to one:

$$\sum_{i=0}^N \lambda_{k,i,t} = 1 \quad (22)$$

- Logical constraints

For $i=1, \dots, N$

$$\left(\sum_{r=0}^N \lambda_{k,r,t} \right) - \lambda_{k,i-1,t} - \lambda_{k,i,t} + N\delta_{k,i,t} \leq N \quad (23)$$

This problem can also be formulated by using the so-called Special Ordered Sets (SOS). The $\lambda_{k,i,t}$ variables can be declared as Type-Two Special Ordered Sets (SOS-2) variables³⁸ in order to exploit their special structure for purposes of computational efficiency (Williams, 1985). In that case, equations 22 and 23 are already implicit in the definition, the binary variables delta will not be used explicitly and, of course, the additional constraints cannot be applied. This alternative, followed by Messner (1997), was not considered here.

³⁸ Special ordered Sets (SOS) are sets of non-negative variables that are required to sum to 1. The variables within a Type Two Special Ordered Set (SOS-2) fulfil the condition that at most two members of the set are positive and if these two are positive they have to be adjacent.

4. Some results from models with endogenous technological change

In this chapter some illustrative analyses are presented with both the ERIS and MARKAL models. A very simple aggregate model of the global electricity generation system is used to examine the dynamics of behaviour when the increasing return mechanism is present and to identify the parameters that influence the outcome. Here, primarily methodological insights are derived. First, the initial experiences with ERIS are described. A comparison between the linear programming (LP), NLP and MIP solutions is made and the parameters affecting the MIP approach are examined. Then, a similar analysis with MARKAL is presented. Sensitivities to the progress ratio, the maximum growth rates and the discount rate are carried out and the possibility of specifying a two-stage learning is discussed. The results presented here are drawn mainly from Kypreos and Barreto (1998a), Kypreos and Barreto (1998c) and Barreto and Kypreos (1999a).

4.1 Description of technologies

The analyses in this and the subsequent chapters have been concentrated on the global electricity generation market. Electricity constitutes one of the most dynamically growing sectors of the world energy system. Global energy trends towards an increasing use of cleaner and more flexible end-use fuels signal a growing role for electricity in the future (IIASA-WEC, 1998). It is also a sector experiencing profound structural changes. Introduction of competition in the electricity markets and growing environmental concerns will affect the technological choice in the industry (Paffenbarger, 1999). Liberalised markets, in particular, will strengthen the pressure for cost competitiveness of generation alternatives. However, the new structure of the markets may provide also opportunities for decentralised, small-scale, more flexible supply options.

On the other hand, electricity production is a significant and growing contributor to CO₂ emissions (Ellis and Tréanton, 1998), where attractive potential exists to implement less carbon emitting generation options. There are a number of supply technologies that may contribute to a progressive decarbonisation of the fuel mix. The highly dynamic growth of the demand, together with the restructuring of electricity markets around the world, mounting environmental constraints, huge capital requirements and the availability of primary resources will certainly exert a significant impact on the technological trajectory the system will follow in the future. Therefore, it is important to examine opportunities for the different competing generation technologies in the global electricity system. In addition, although information concerning observed or estimated learning parameters is available in the literature for a few other energy technologies, most of the data appear to be concentrated in electricity generation technologies. Thus, this constitutes a convenient example both from the point of view of data availability and policy relevance.

In the exercises presented in this chapter the competitiveness of different generation alternatives is examined in a very simplified single-region model of the global electricity system. An extension to multi-regional models is carried out in subsequent chapters. The

basic parameters for the technologies considered are shown in Table 1. Cost figures are in 1998 US dollars. Unless specified otherwise, a discount rate of 5% is used in all calculations. The characteristics of the technologies and the demand projection are common to both the ERIS and MARKAL exercises.

The demand corresponds to the global electricity generation in the scenario B of IASA-WEC (1998), which is a "middle-course" trajectory of the global energy system. In such scenario, electricity grows at an average rate of 1.6% per annum between 1990 and 2050.

Technology	Abbrev	Inv. Cost (US\$/kW)	Fixed O&M (US\$/kW/year)	Var. O&M (US\$/kWyr)	Efficiency (Fraction)	Progress Ratio
Conventional Coal	HCC	1357	69	22.7	0.39	1
Advanced Coal	HCA	1584	67.5	23.6	0.45	0.94
Gas Steam	GSC	987	50.6	17.7	0.41	1
Gas CC	GCC	600	36.6	19.7	0.51	0.89
Gas Turbine	GTC	350	58.5	16.03	0.36	1
Gas Fuel Cell	GFC	2463	43.5	105.1	0.65	0.81
Oil Steam	OLC	1575	63.6	18.13	0.38	1
Nuclear	NUC	3075	114	5.91	0.34	1
New Nuclear	NNU	3400	114	5.91	0.36	0.96
Hydro	HYD	3562	49.5	3.9	0.70	1
Solar PV	SPV	4600	9.	39.4	0.1	0.81
Wind	WND	1035	13.5	26.3	0.33	0.88
Geothermal	GEO	3075	7.8	92	0.3	1

Table 1. *Main characteristics of electricity generation technologies.*

Six technologies are considered to have a progress ratio lower than one: Solar photovoltaics, wind turbines, gas fuel cell, combined cycle gas turbines, advanced coal and new nuclear power plants. Figure 9 presents the corresponding learning curves applied. For the segmentation with the MIP approach a maximum cumulative capacity³⁹ of 6000 GW and eight segments were considered for the piece-wise approximation of all the learning curves. For the other technologies investment costs are assumed constant along the horizon (i.e. progress ratio is considered equal to one). Maximum growth constraints for the capacity are used to control the penetration of the technologies.

Although no attempt is made to fully justify the progress ratio values used here, they are within the usual ranges reported in the literature. Along the different analyses presented in this document, the progress ratios of some technologies have been slightly adjusted as to reflect new or more complete information the author was made aware of. Whenever changes are made, they are indicated. As discussed above, there is uncertainty concerning learning parameters and technology characteristics. Therefore, these results should be regarded much more as what could happen if progress could be sustained at such pace. A further question would be which actions should be required in order to ensure that these trends take place. Uncertainty in the learning rates is addressed below in section 5.5.3.

³⁹ In this scenario none of the learning technologies considered was reaching the upper bound imposed by the maximum cumulative capacity.

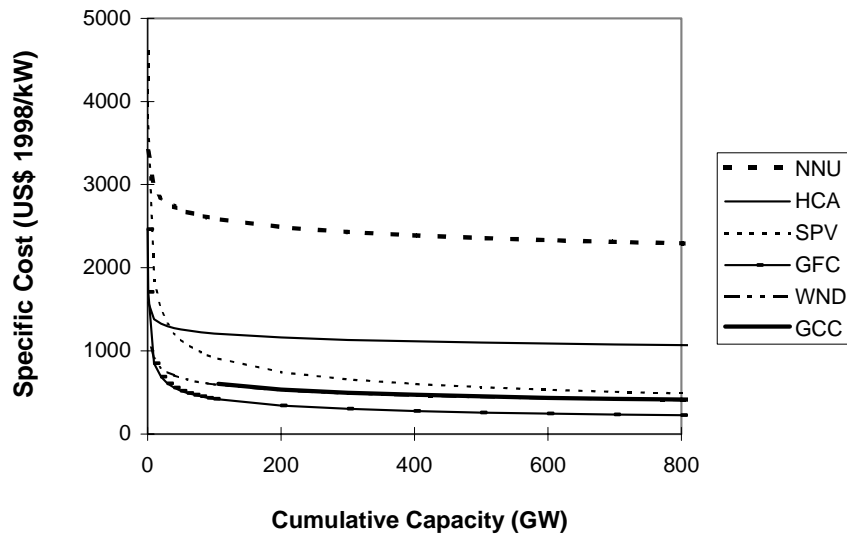


Figure 9. *Learning curves for different technologies.*

4.2 First experiences with the ERIS model prototype

The ERIS model prototype was created within the TEEM (1997, 1999) project as a tool to test different formulation approaches and solution methods, regarding endogenous incorporation of technological change in energy models. It provides a straightforward way of testing new concepts before translating them to more complicated models and allows assessing their advantages, disadvantages and implementation difficulties.

The development of the model has been a joint effort between several partners. The original prototype was formulated by Messner (1998) and coded and tested by Capros et al. (1998a) as a Linear Programming (LP) version and a Non-linear Programming (NLP) one, which included a non-linear formulation of learning curves. The prototype was extended by Kypreos (1998) to include stochastic and risk aversion options and more general constraints. Kypreos and Barreto (1998a) implemented the Mixed Integer Programming formulation of learning curves. A further extension of the model including a regional index and trade of energy carriers and emission permits has been implemented and used in Barreto and Kypreos (2000). A brief description of the model is given in Appendix 2. A more detailed one can be found in Kypreos et al. (2000).

In this section the model is used to examine the influence of several parameters in the MIP approximation and to illustrate the significant differences that the inclusion of endogenous learning produces in the structure of the solution as compared to the exogenous cost specification.

4.2.1 Comparison between LP, NLP and MIP solutions

The comparative results of the ERIS model presented in this section illustrate the impact of technological learning on the structure of the simplified global electricity system used as example⁴⁰. A comparison between the static LP, NLP and MIP solutions is presented⁴¹.

Two different CO₂ scenarios were considered. An unconstrained "Business-as-Usual" one and a CO₂ constrained scenario, where from the year 2010 onwards, emissions of the electricity system must remain stabilised at 1990 levels. However, for simplicity, most examples are presented for the CO₂ constrained situation.

Figure 10 compares the global generation mix for the year 2050 under the CO₂ constrained scenario. Figure 11 to Figure 13 depict the corresponding electricity generation along the time horizon with each version of the model. In the LP model the system relies mainly upon combined cycle gas turbines to supply the demand. Conventional nuclear plants and, to a less extent, wind turbines are the main contributors to fulfil the CO₂ target. In the NLP model, gas combined cycle still constitutes the main supply option. Conventional nuclear technology is displaced by an increase in wind turbines output and, to a less extent, new nuclear plants. In the MIP model, solar photo-voltaics is massively introduced and the gas combined cycle plays a much more reduced role. By the end of the time horizon, solar PV, together with wind turbines and advanced coal plants, has experienced a significant growth.

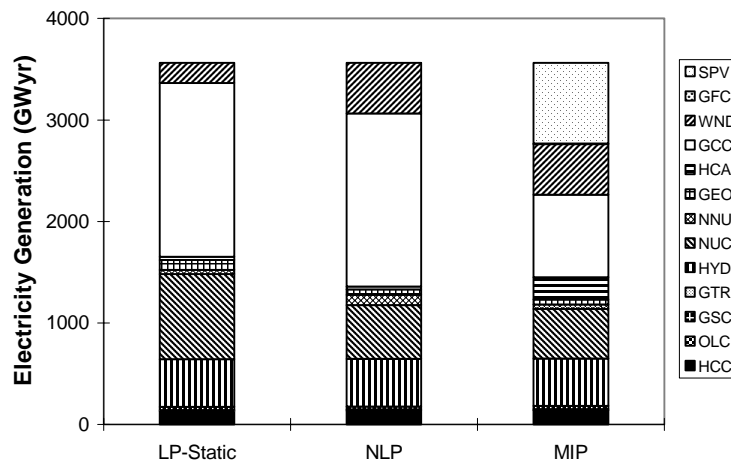


Figure 10. Comparison of electricity generation in 2050. CO₂ constrained scenario.

⁴⁰ Model runs were performed with the CPLEX 6.0 solver for LP and MIP problems and the MINOS5 solver for NLP problems. For the MIP problems, following the recommendation of Mattsson (1997), the VARIABLESELECT parameter, used to specify the rule for selecting the branching variable at the node selected for branching (ILOG, 1997), was set to 'strong branching'. This allowed a faster computation.

⁴¹ Here the LP model where the technologies have constant, time-independent investment costs is referred to as static LP model.

The differences in the structure of the electricity generation systems resulting from the non-learning LP and the NLP and MIP learning versions are evident. Under the assumed learning patterns, the models with learning favour the introduction of new technologies hardly considered by the LP-static model. Up-front investments are performed in order to render them competitive in the long term. There is also a clear difference between the local optimum obtained in this case with the NLP model and the global optimum obtained with the MIP one. From the experience with the NLP model, it was established the necessity of applying the MIP formulation in order to identify better (global optimum) solutions. It was noticed, however, that the models with learning (both MIP and NLP) react in a very sensitive way to the assumptions both on progress ratios and other parameters.

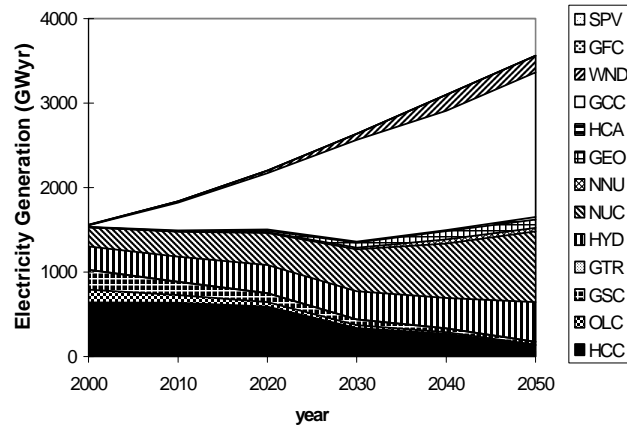


Figure 11. *Electricity generation. LP model. CO₂ constrained scenario.*

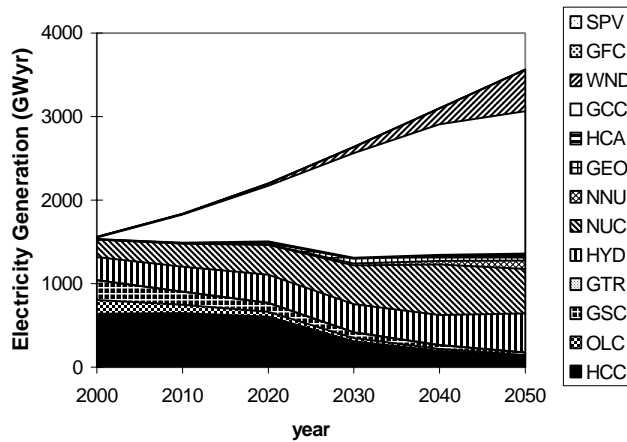


Figure 12. *Electricity generation. NLP model. CO₂ constrained scenario.*

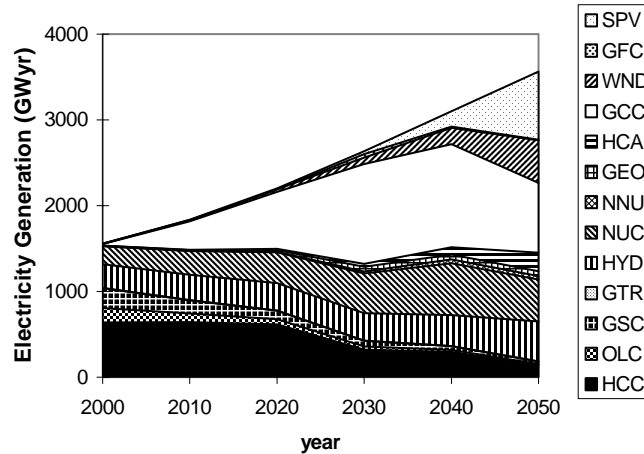


Figure 13. Electricity generation. MIP model. CO₂ constrained scenario.

Table 2 summarises the objective values for the Business-as-Usual and CO₂ constrained scenarios using the different formulations. An indicative of the error involved in the MIP approximation is also presented (in parenthesis). It is computed following a procedure reported by Mattsson (1997). After the optimisation, the total discounted cost of the MIP solution is computed again, using the original non-linear curves to calculate the investment costs corresponding to the learning technologies. This provides the correct estimation of the cost. The difference between this value and the original MIP objective gives a measure of the accuracy of the MIP approximation. When the difference is small the approximation can be considered adequate.

Model	BaU	CO ₂ stabilisation
LP	8759498.14	8849840.0
NLP	8647366.39	8683280.8
MIP	8638750.95 (0.2%)	8668759.98 (0.19%)

Table 2. Objective function of the different alternatives.

The total discounted costs are, in general, reduced in the NLP and MIP solutions as compared to the LP formulation. If the assumptions on progress ratios can be supported for the range of installed capacities estimated in the model, this could be an indicative that lower estimates of CO₂ mitigation costs may be expected when models with endogenous learning are applied and low-carbon technologies are allowed to learn.

The MIP formulation is able to provide lower objective values than the NLP one. As for the resulting technological choice, in some cases the local optimum solutions found with the NLP model provided a technology mix similar to the MIP one, but in other cases the structure of the energy system was significantly different.

When the NLP was solved again using the MIP solution as starting point, better optima for several of the NLP problems were found. In several cases the resulting technology mix of

this restarted NLP solution was indistinguishable from the MIP one. Table 3 presents the new NLP optimum and the percentage reduction respect to the previous one.

	BaU	CO ₂ Stabilisation
Objective value	8642374.3	8674556.3
Reduction (%)	0.06%	0.1%

Table 3. *New NLP objective values if restarting from MIP*

It must also be mentioned that for some of the particular tests with this small-scale problem, the NLP model (without restarting from the MIP solution) was already able to find very good solutions. However, other experiences using MARKAL (Kypreos and Barreto (1998d) or Seebregts (1998), the latter with a large scale database) did not provide such results, with the NLP problem even behaving in an unstable way in some cases.

Valuable information about the progress experienced by the learning technologies is provided by the evolution of the specific cost along the time horizon. As an example, Figure 14 presents such evolution for the solar photo-voltaics technology in the CO₂ constrained scenario, when using the MIP piece-wise formulation.

For the piece-wise approximation the specific cost in each period is computed as the quotient between the investment costs $IC_{k,t}$ and the new capacity installed per period ($INV_{k,t}$). As a comparison, the specific cost obtained using the continuous expression of the learning curve for the same cumulative capacities is also presented⁴². As it will be seen below (numeral 4.2.2), the values estimated depend on the way the curve has been segmented. In this particular case, with the piece-wise approach, a different value was obtained in each time period. This means that enough capacity was installed as to make the technology change to a different (lower cost) segment of the curve in each subsequent period.

Under the learning conditions specified here, by the end of the time horizon the investment cost of solar photo-voltaics in this scenario has reached the fairly low value of 340 US\$/kW. This behaviour has raised the question, whether the cost reduction of some learning technologies should be limited, for instance providing a lower bound for the specific cost, in order to avoid excessive cost reductions. In previous analyses, different criteria have been applied to handle this situation. Messner (1997) imposed a lower bound for the specific cost of the learning technologies, while Mattsson (1997) decided to let the natural saturation of the learning curve to control the cost reduction without imposing any lower bounds, as is done in the runs reported above.

⁴² Notice that here the comparison corresponds only to the specific costs that are obtained if the expression $SC=aC^{-b}$ is used. This should not be confused with using the non-linear formulation (NLP) model, which in fact, as already seen, provides a different technological mix.

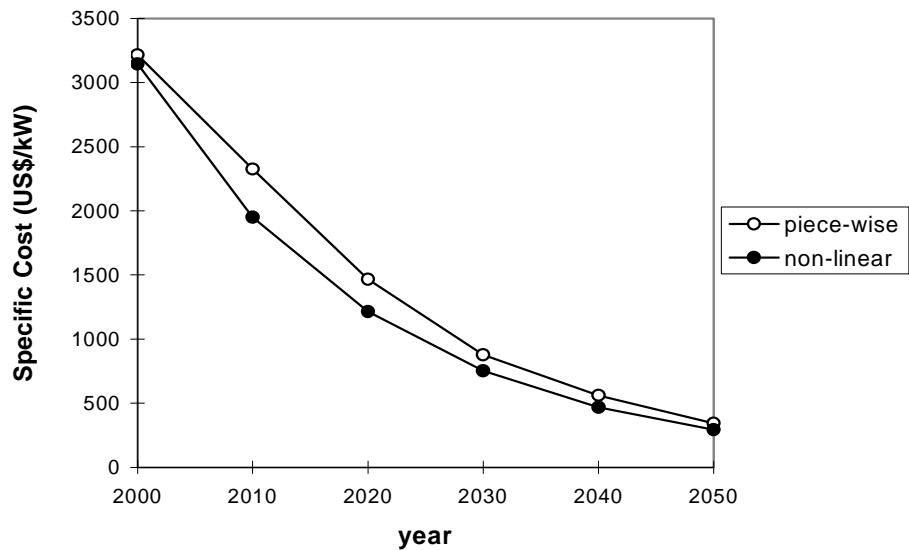


Figure 14. *Evolution of specific cost for SPV. Piece-wise and continuous curves.*

Specifying a lower bound or "floor" investment cost will provide a saturation effect of the learning process additional to the normal saturation of the curve itself, which, as already mentioned, is provided by the fact that, as markets saturate, it is more difficult to reach new capacity doublings. This lower bound would correspond to the expected cost of the technology in its mature stage. It should, however, if possible, be supported by studies of the cost structure and specific potential for cost reductions in the different components. Nonetheless, it will still be tied to the expectations of the modeller as to what constitutes a "reasonable" limit value.

4.2.2 Influence of some parameters on the MIP approach

The accuracy and efficiency of the MIP linearisation approach are affected by several factors. Using the simplified global electricity generation ERIS model, the influence of the segmentation procedure, the maximum cumulative capacity and the number of segments is analysed here.

4.2.2.1 Segmentation procedure

The procedure to segment the cumulative cost curve has effects on the computation and must be defined carefully. An efficient segmentation must approximate as well as possible the shape of the original curve. After some tests a specific procedure with variable length segments was chosen for the analyses presented in this document. Such rule (already described in the numeral 3.6) is compared here with a simpler one applying equally spaced breakpoints in the cumulative cost axis.

The rationale for the variable length segmentation comes from the shape of the experience curve itself. The cost reduction is very significant for the first units installed but afterwards the learning effect slows down and saturates. Therefore, a higher estimation error is more

likely for the first segments. It seems reasonable to use a segmentation procedure with shorter segments at the beginning and increasingly longer segments afterwards, in order to obtain a better representation for the first region of the curve.

As explained before, the piece-wise linearisation is carried out on the total cumulative cost curve. However, a good visualisation of the approximation is obtained when the equivalent step-wise specific cost curve is inspected. Figure 15 presents the resulting stepwise specific cost curve with the two segmentations (8 segments and a $C_{k,max}$ of 6000 GW in both cases).

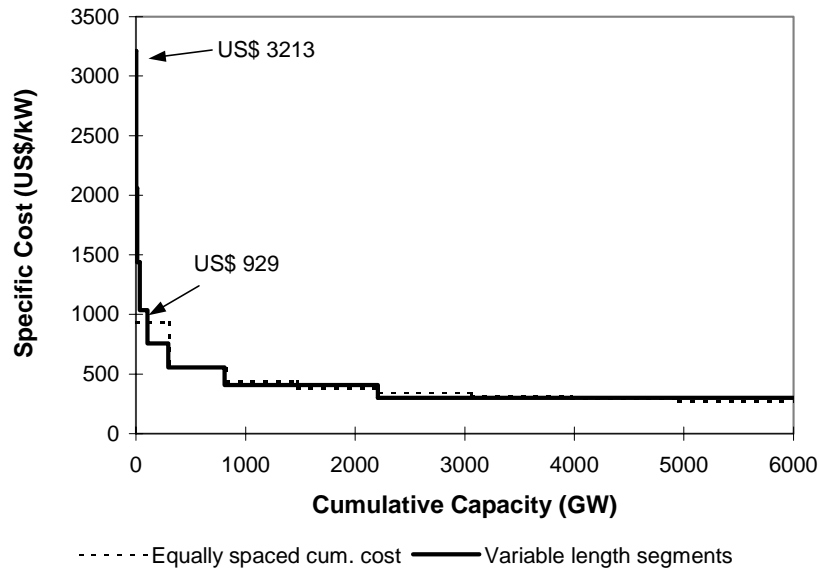


Figure 15. *Alternative variable-length Vs equally spaced cumulative cost segmentation procedures*

The estimated specific cost corresponds to the slope of every linear segment of the cumulative cost curve. Thus, the first segment has a much lower value than the real starting cost ($SC_{k,0}$) in the original non-linear experience curve. This underestimates the cost for the first units. Such effect is more significant for technologies with higher learning rates because they exhibit a faster initial decay. Besides the number of segments the segmentation procedure also plays here a significant role. The variable length rule provides better estimates for the first segments and fits better the shape of the curve. It is relatively insensitive to the variations of the $C_{k,max}$ (see Figure 18 below) and the number of segments, but it is stable and appears to be a good compromise. In fact, increasing the number of segments will basically add a new point to the first region of the curve, improving the estimate of the first segments, but the other ones will not be significantly changed. The decrease of $C_{k,max}$ will provide a higher cost estimate for the first segments.

Other segmentation approaches can be used. A segmentation based on the logarithm of the cumulative cost is used in Seebregts et al. (1998) and Mattsson (1997) reports a procedure intended to achieve a more efficient segmentation, using two different values of maximum capacity to define the breakpoints. However, there will always be a trade-off between the

accuracy of the representation of the different zones of the curve and this should be borne in mind by the analyst.

4.2.2.2 Number of segments

The number of segments influences the precision of the approximation and the solution time. A higher number of segments provides a better representation, but the time for solving the model will increase as the number of binary variables increases. Thus, its choice will be a compromise between the precision required and the computational capability available. The number of segments required can be different depending on the starting point of the learning curve for a given technology. A new technology with high learning potential may require more segments than a mature one, which is already well advanced in its own curve.

Being the cumulative cost curve concave, the linearised approximation provides values under the real cumulative costs (see Figure 16 for an schematic example), driving to underestimation of the investment costs. Due to this, the MIP solution corresponds to a lower bound for the global optimum of the original non-linear problem. As the number of segments is increased, the gap is reduced, deriving in higher estimates for the investment costs, which result in an increase of the objective function.

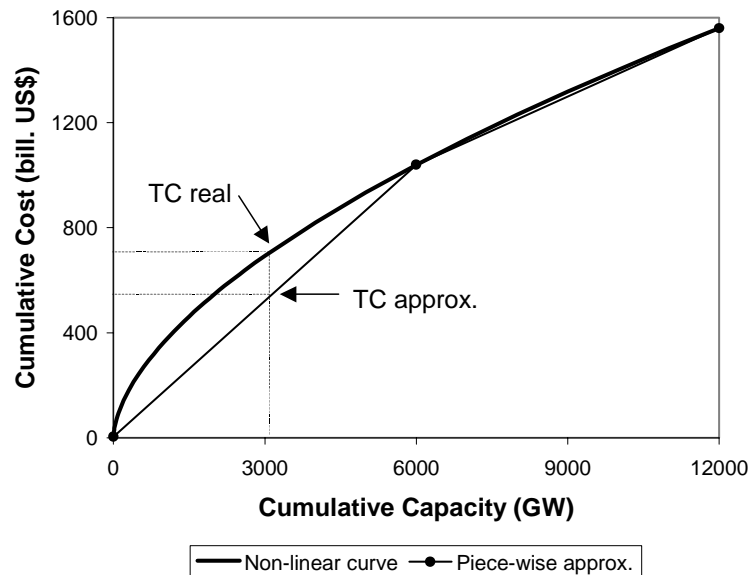


Figure 16. Comparison between real and approximated cumulative cost.

As an example, Table 4 presents the changes on the objective function (total discounted system cost) in the CO₂ constrained scenario for different numbers of segments. Percentage changes are given respect to the eight segments case. The variable length segmentation is applied and all technologies have the same number of segments. In these particular tests, the variation of the number of segments within this range did not alter the structure of the solution.

Number of segments	Objective Function	Change (%)
5	8663690.6	-0.06%
6	8666096.7	-0.031
7	8667765.6	-0.011%
8	8668759.98	0%
9	8669231.1	0.005%
10	8669435.9	0.008%

Table 4. Variation of the MIP objective value with the number of segments.

4.2.2.3 Maximum cumulative capacity

The maximum cumulative capacity ($C_{k,max}$) provides an upper bound for the cumulative installations of a given technology and also affects the segmentation. For the same number of segments, a lower $C_{k,max}$ value may provide a better representation. The partition will be such that the corresponding steps will have higher specific costs, although the intervals of cumulative capacity are smaller. The effect of $C_{k,max}$, however, depends on the segmentation rule applied. Some segmentation patterns are more sensitive than others. Figure 17 and Figure 18 show comparative examples. The variable length rule is much less sensitive than the equally-spaced-cumulative-cost one. Nonetheless, changes are still perceptible, as the "amplification" in Figure 19 shows.

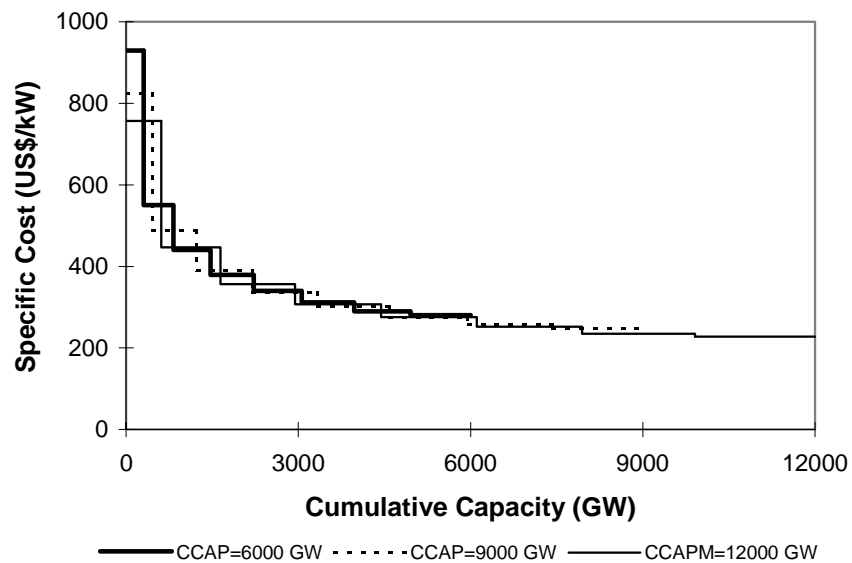


Figure 17. Specific cost segmentation for different maximum cumulative capacities. SPV Technology. Equally spaced cumulative cost rule.

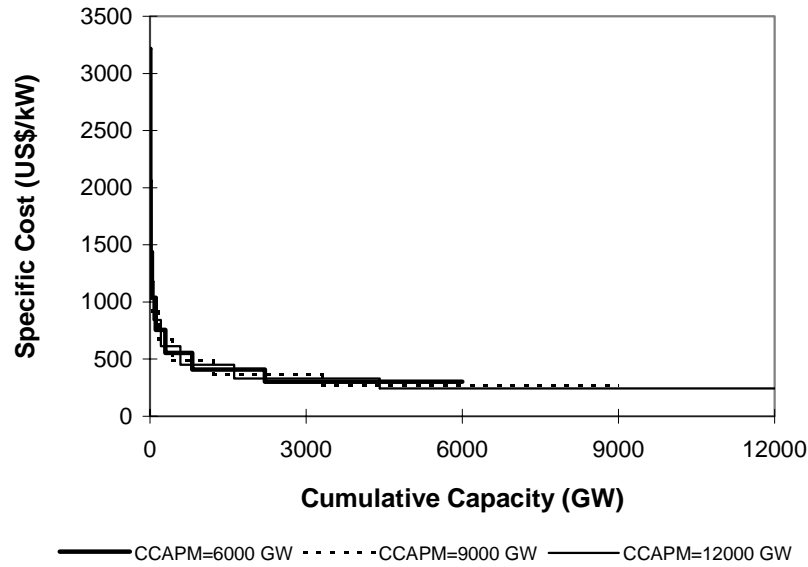


Figure 18. *Specific cost segmentation for different maximum cumulative capacities. SPV Technology. Variable length rule.*

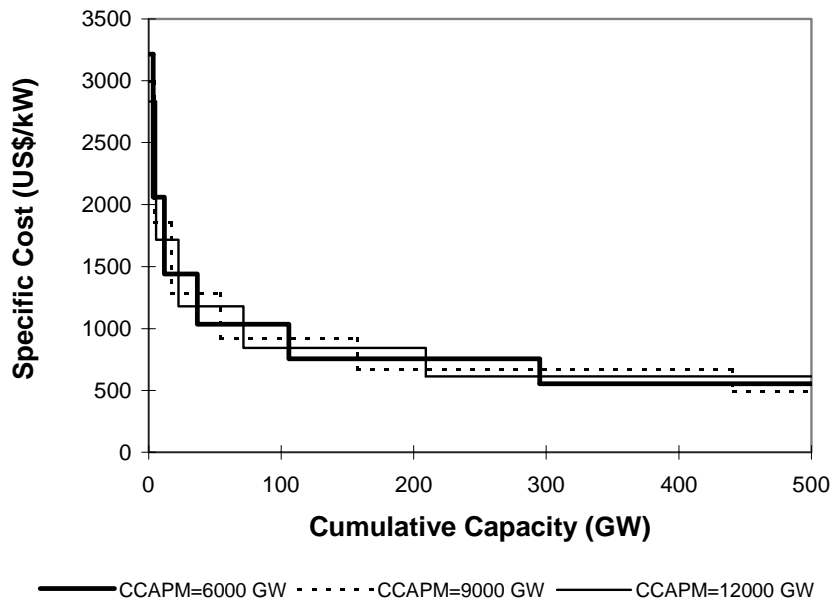


Figure 19. *Specific cost segmentation for different maximum cumulative capacities. SPV Technology. Variable length rule. "Amplified" scale.*

No significant changes in the MIP objective function were observed for any of the $C_{k,max}$ values considered here, as is shown in Table 5. Percentage variations are presented in relation to the $C_{k,max} = 6000$ GW case.

$C_{k,max}$	BaU		CO ₂ stabilisation	
	variable length	equally spaced TC	variable length	equally spaced TC
6000 GW	8638750.9	8624093.8	8668759.9	8654089.0
9000 GW	8637268.6	8617419.9	8668719.9	8654517.2
Change (%)	-0.017	-0.077	-0.0005	0.005
12000 GW	8639565.6	8614437.7	8669990.5	8641479.1
Change (%)	0.01	-0.112	0.014	-0.146

Table 5. Variation of the MIP objective value with $C_{k,max}$.

The capacity installed and the output of a given technology along the horizon may be affected when $C_{k,max}$ is modified. As a result of the higher specific cost steps when $C_{k,max}$ is lower, investments on a particular technology could be lower or occur later. However, it is not easy to determine what the exact effect will be and its magnitude also depends on the way the curve is segmented. Figure 20 and Figure 21 present the electricity generation mix in the year 2050 when different values of cumulative capacity are specified under the two segmentation rules described above. In this case, the variable length segmentation method provided a more stable approximation. In this exercise, the basic structure of the solution was not significantly altered when $C_{k,max}$ was modified.

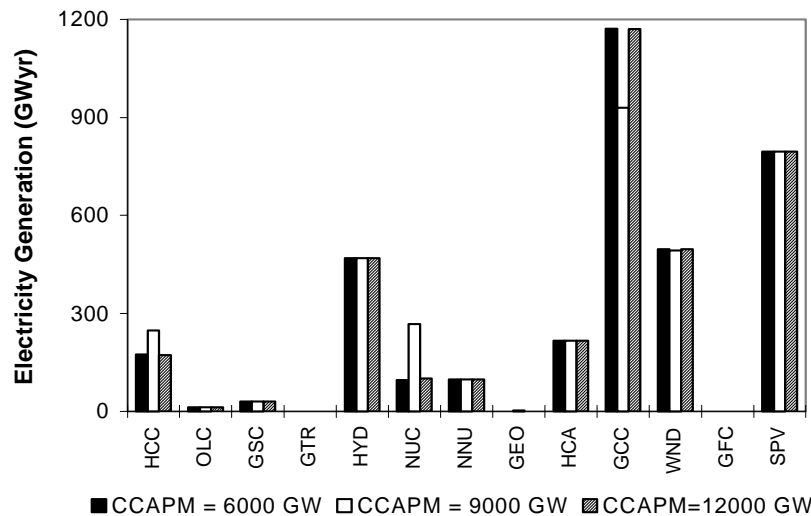


Figure 20. Electricity generation mix in 2050. Different $C_{k,max}$. Equally spaced cumulative cost segmentation.

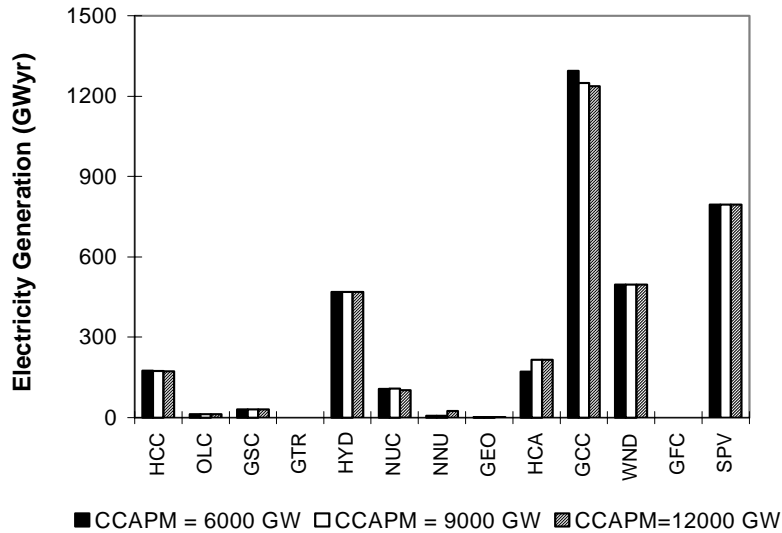


Figure 21. Electricity generation mix in 2050. Different $C_{k,max}$. Variable length segmentation.

The variations may not be particularly significant but they still exist. In fact, the sensitivity of the solution to the $C_{k,max}$ (and to the other parameters) also depends on whether the learning technology is marginally used or not. Marginal technologies are much more sensitive to variations. On the other hand, when a given learning technology is sufficiently attractive, such that it is installed along its maximum growth constraint due to the "lock-in" effect, moderate variations of the parameters will barely affect its installed capacity or output. Nevertheless, it is important for the analyst to bear in mind the assumptions applied.

Therefore, sensible values have to be assigned for $C_{k,max}$. Of course, the ultimate criterion corresponds to the estimated potential for a certain resource or technology according to technical, economic and environmental criteria but below this upper bound a convenient value has to be chosen which fits the particular conditions. A reasonable starting value may be used for a first preliminary run and, according to the evolution of the technology under different scenarios, adjusted for the subsequent ones. A value sufficiently high for a reference scenario may not be adequate for another scenario where the same technology has a higher penetration. Therefore, a consistent value should be chosen in order to keep the same piece-wise cost approximation across the different scenarios.

4.3 A simple global electricity MARKAL model with endogenous learning

MARKAL is a dynamic linear programming "bottom-up" model for energy systems (Fishbone and Abilock, 1981). It was developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) and is widely used for national and multi-national analyses in a number of countries (see, for instance, Kram, 1993). It is a technology-oriented model, allowing a rich representation of supply and demand technologies, helpful to identify future cost-effective technological options and assess their role in the energy system under different conditions (e.g. the fulfilment of

environmental restrictions)⁴³. As mentioned before, following the same formulation used in the ERIS model, learning curves were also incorporated in the MARKAL energy optimisation model. Incorporation of technological learning is an important step to improve the consistency of mechanisms of technological change in the MARKAL family of models. Experiences with MARKAL incorporating the learning curve endogenisation implemented here have been reported for a small-scale global electricity system (Kypreos and Barreto, 1998c) and a multi-regional global electricity system (Barreto and Kypreos, 2000b) and for a large scale European database (Seebregts et al., 1998, Seebregts et al., 2000a).

Using the same technological database described above, some exercises performed with MARKAL with endogenous learning are presented here. As before, the system analysed represents the global electricity market and the demand for electricity corresponds to the IIASA-WEC (1998) scenario B. The competitiveness of different generation alternatives is examined applying the MIP-learning and the static LP models. Sensitivities to the learning rates are performed and the inclusion of a two-stage learning approach is discussed.

Regarding CO₂ emissions two scenarios are considered. A Business-As-Usual scenario (BaU) represents the unconstrained reference development. A CO₂ stabilisation scenario (Sta) imposes a constant 5% reduction in relation to the 1990 levels from 2010 onwards. This is of course a very strong constraint for the electricity system alone, but it is used here only to illustrate the response of the model. Maximum growth constraints for the capacity are used to control the penetration of technologies. The gas fuel cell and solar PV are allowed to grow at maximum 15% per annum. The other learning technologies have a maximum growth rate of 10% per year.

4.3.1 Static linear programming Vs MIP learning

The model outcomes of the linear programming MARKAL with constant investment costs for all the technologies and the MIP model with the reference learning conditions are compared here.

Figure 22 presents the evolution of the electricity generation mix in the Business-As-Usual scenario for the static-LP and MIP models. There are significant differences in the structure of the resulting energy systems. In the LP model mainly coal (conventional and advanced) and gas-fired combined cycle plants provide electricity by the end of the horizon. The latter becomes the dominant technology by 2050. Wind turbines are already competitive and penetrate the market. In the learning case, reliance on coal technologies is lower and wind turbines and solar PV have a higher contribution. Already in the BaU scenario the MIP learning model finds cost-effective the introduction of solar photo-voltaics not considered by the static-LP approach.

⁴³ A description of the basic structure of the MARKAL model can be found in Berger et al. (1992).

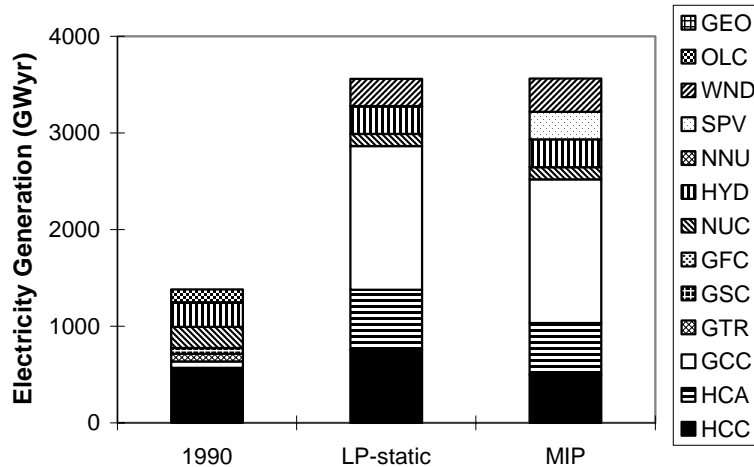


Figure 22. *Generation mix for the BaU scenario in 2050.*

A more detailed view of the electricity generation obtained with the MIP model for the Business-As-Usual scenario (BaU) is presented in Figure 23. Conventional coal is still a very important generation technology, declining by the end of the horizon when new technologies have grown enough to make their contribution noticeable.

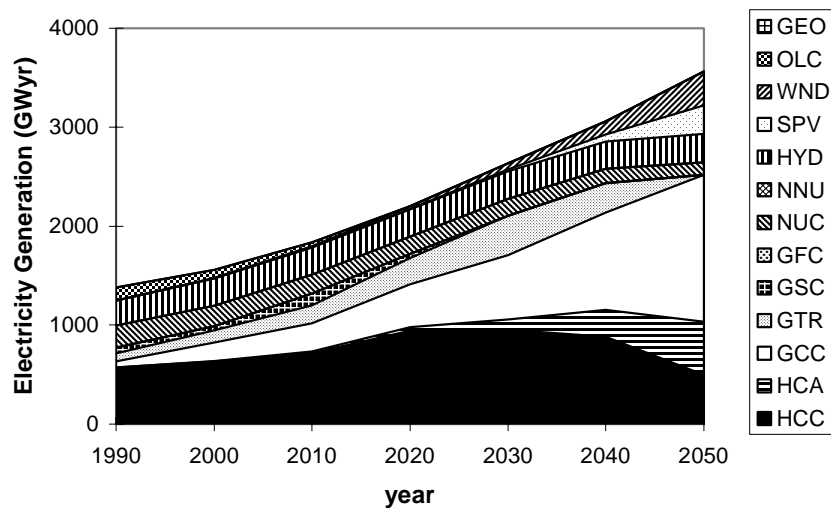


Figure 23. *Electricity generation - MIP Model - BAU scenario.*

Figure 24 presents the comparison of the corresponding emissions in the BaU scenario and the CO₂ target imposed. Due to the introduction of new, cleaner technologies, the emissions of the MIP-learning model in the BaU scenario are below those of the static-LP model. This is a result arising from the presence of endogenous technological learning. Particular technological trajectories chosen by the model may drive to reduction of emissions without the imposition of an exogenous constraint.

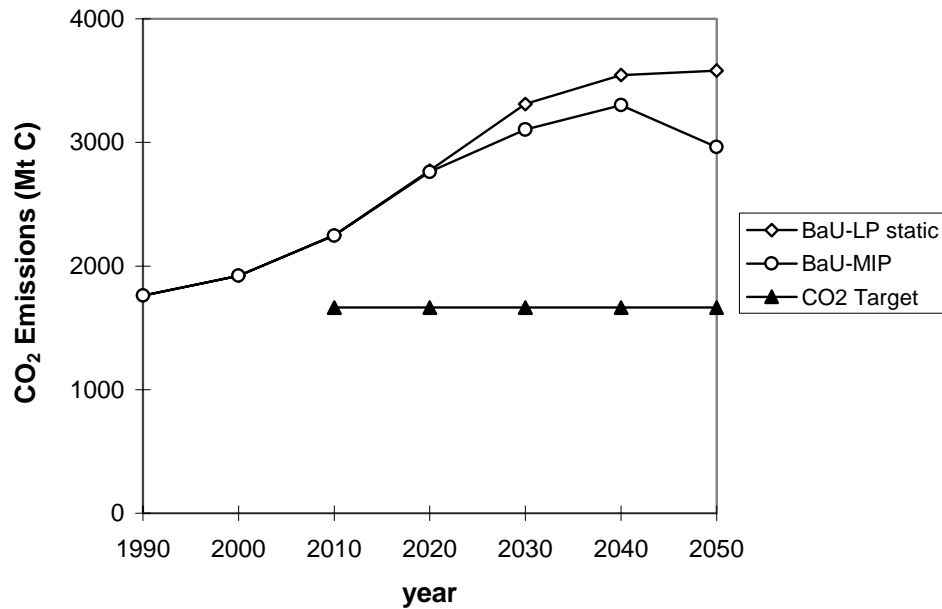


Figure 24. Comparison of CO₂ emissions. LP static Vs MIP.

Figure 25 presents the comparison between the static-LP and the MIP-learning evolution of the electricity generation mix for the stabilisation scenario (Sta) in 2050. In the LP case, the system relies on gas combined cycle plants, conventional nuclear plants and wind turbines for fulfilling the target. The MIP learning model provides a more diversified system. In addition to the mentioned technologies, Solar PV, already growing at the maximum growth rate in the BaU case, gas fuel cells and new nuclear power plants are also introduced. In both cases, the gas combined cycle turbine becomes the dominant technology and coal generation is almost phased out by the end of the horizon.

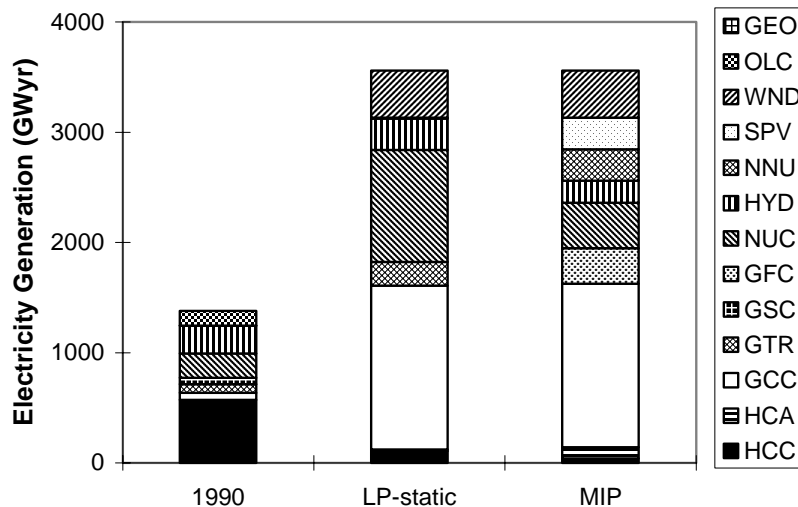


Figure 25. Generation mix for the stabilisation scenario in 2050.

A more detailed view of the electricity generation obtained with the MIP model for the stabilisation scenario (Sta) is presented in Figure 26.

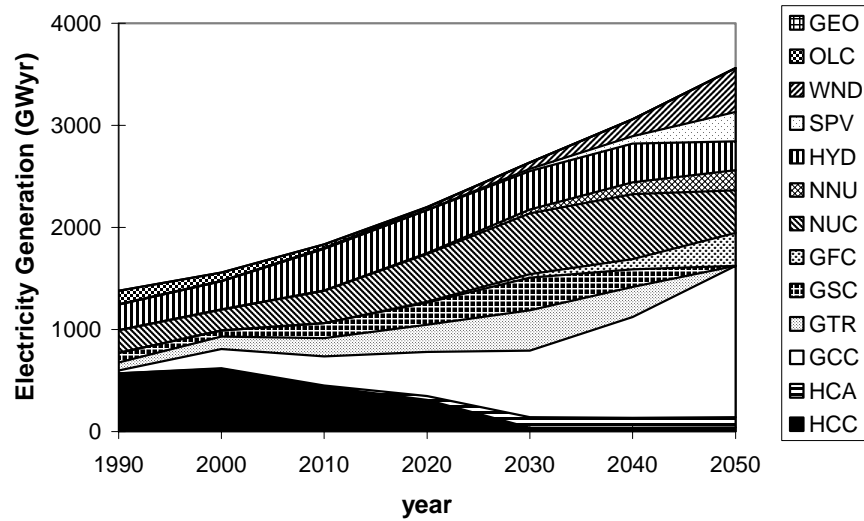


Figure 26. *Electricity Generation - MIP Model- Stabilisation scenario.*

Another interesting comparison is the total discounted system cost. Cumulative investments are reduced in the endogenised learning case as compared to the static-LP one. A comparison of the mitigation costs, computed as the difference between the total system cost for the stabilisation scenario and that of the BaU one reveals that learning provides a reduction of 9.1% with respect to the LP-static case. This is an interesting result, in agreement with the statement that earlier investments on new low-carbon or carbon-free technologies, although more expensive now, could prove beneficial in the long run, driving to lower costs of CO₂ abatement in the global energy system.

Scenario	LP-static	MIP-Learning	% Reduction
BaU	15099313	14934098	1.1
Sta	15992757	15745840	1.54
Mitigation Cost	893444	811742	9.1

Table 6. *Comparison of total discounted system cost (Million US\$ 1998).*

4.3.2 Sensitivity to the progress ratio

The progress ratio constitutes one of the key and most sensitive assumptions when endogenising learning curves in energy optimisation models. Technological learning processes are significantly uncertain (Grübler, 1998) and, therefore, the specification of this parameter is not an easy task. Historical estimates depend on data sets, time span and performance indicators used (Schrattenholzer, 1998a) and it is very difficult either to ensure that the observed trends will continue in the future or to foresee if (and how) new developments will cause an alteration of the learning trajectory. The technology could reduce its learning rate as it approaches the commercial stage or may increase it, for

instance by higher R&D expenditures or breakthroughs in generic technologies affecting its development. In Seebregts et al. (1998) a number of issues that may affect the technology development and the derivation of a consistent progress ratio are discussed.

Due to the uncertainty, it is advisable to conduct sensitivity or stochastic analyses. Here, some sensitivity analyses are carried out for the system presented above. Stochastic analyses considering uncertain learning rates are performed in the numeral 5.5.3 below.

The sensitivity values for the progress ratio are presented in Table 7. For the Advanced Coal and New Nuclear technologies the case where no learning exists was considered as sensitivity, given that these technologies are subject to environmental and safety concerns that may prevent them to achieve cost reductions. For each run the progress ratio of only one technology was modified, keeping the others their reference values. A comparison of the resulting electricity generation per learning technology under both the BaU and Sta scenarios is presented in Figure 27.

	Lower	Reference	Upper
Advanced Coal	0.88	0.94	1.0
Gas CC	0.84	0.89	0.94
Gas Fuel Cell	0.75	0.81	0.87
New Nuclear	0.92	0.96	1.0
Solar PV	0.72	0.81	0.85
Wind	0.81	0.88	0.94

Table 7. *Sensitivity values for the progress ratio*

Solar PV was already attractive under the previous conditions both in the stabilisation and the BaU scenarios, growing along its maximum growth constraint. If the progress ratio is decreased (i.e. faster learning), the technology will also grow along its maximum growth constraint. When the progress ratio is increased to 0.85, the technology is not installed at all under the unconstrained scenario. A progress ratio of 0.85 is not attractive enough and the technology, not being forced into the solution by a CO₂ constraint, is "locked-out" from the system. However, it grows again at maximum under the constrained scenario.

No significant variation resulted in the penetration of the wind turbine and the gas combined cycle under the range of progress ratios considered here. This is not surprising given that these technologies were already competitive even in the static LP model (no learning). They are robust options for both the learning and the non-learning model.

The gas fuel cell, on the other hand, is more sensitive. With PR =0.81, the technology was not competitive for the BaU. An increase of PR to 0.87 makes it even less competitive. When the progress ratio is decreased to 0.75, the technology is introduced in the BaU situation. In the CO₂ constrained case, the technology grows along the constraint for the three progress ratios considered.

Advanced coal and new nuclear plants are also significantly affected. A no learning situation would leave these two technologies in competitive disadvantage and with a marginal market share. When the progress ratio is 1.0, the advanced coal plant is still a competitive alternative to conventional coal plants in the BaU situation, but its penetration is lower. Under the stabilisation scenario, coal is phased out and advanced coal penetrates less than in the BaU case, but also here the difference is evident. Without learning the technology plays only a marginal role. The new nuclear technology is not competitive under the BaU scenario and reduces its growth drastically in the stabilisation one if no learning is allowed.

As expected, the results of the model with endogenous technological learning are sensitive to the learning rates being assumed. If the value of the progress ratio is not attractive enough, the technology may be "locked-out" of the system. The specific effects, however, seem to be case and technology dependent. Non-competitive, marginally used technologies are more sensitive to progress ratio (and other) assumptions. The sensitivity analyses are useful to study which would be the "break-even" progress ratio for a particular technology. That is, the progress ratio that, other things equal, will make the technology competitive under particular conditions.

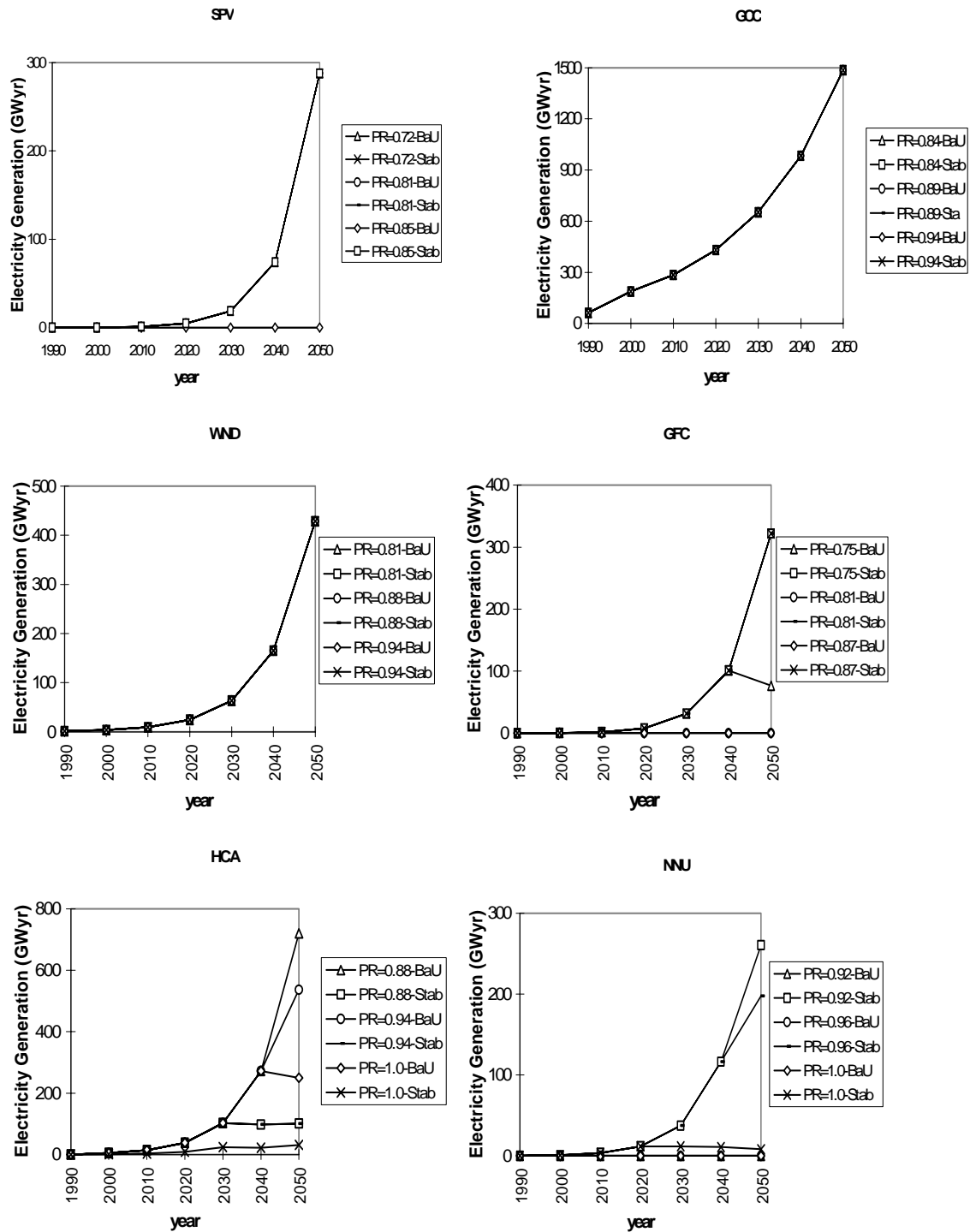


Figure 27. Sensitivity to the progress ratio.

The maximum growth rates are also very influential in the penetration of learning technologies. They affect the potential of a technology to learn along the time horizon⁴⁴. Thus, they determine to some extent whether or not a variation is observed when the progress ratio is changed.

In order to illustrate their influence, Figure 28 presents the variation of the electricity generation under the stabilisation scenario when the maximum growth rate of the solar PV is modified from 10% to 20% per year. With a low growth rate, the technology may not have the opportunity to accumulate enough capacity to become cost-effective. There is not sufficient learning potential along the time horizon and it can be "locked-out" from the system, as it occurs here when the growth rate is 10%. However, if the technology is allowed to grow at a faster rate, the potential to reach lower costs is increased and it may result attractive. Once a learning technology becomes competitive, the MIP-learning model will try to install it up to the maximum, in order to fully profit from the cost reduction potential. This is evident here with the increasing (although possibly unrealistic) role played by solar photo-voltaics if it is allowed to grow at 15, 17 or 20% per annum.

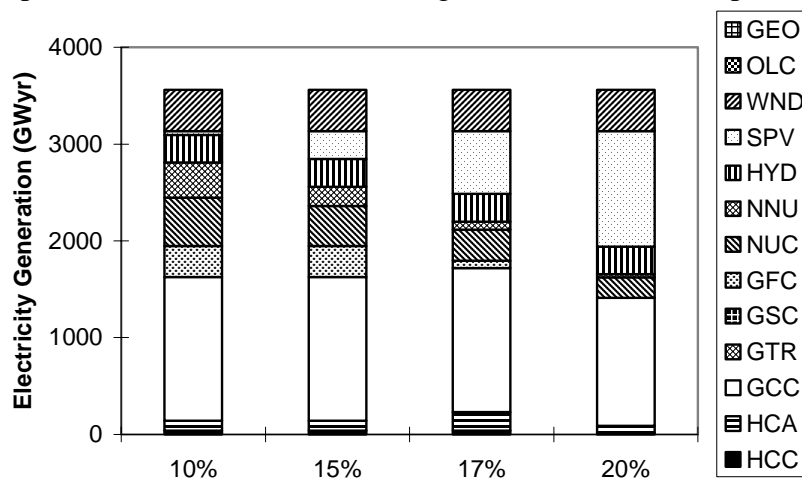


Figure 28. Generation mix in 2050-Stabilisation scenario. Different growth rates for SPV.

⁴⁴ The maximum growth constraints are introduced in the model to mitigate the "bang-bang" behaviour typical of linear programming models and provide a more realistic penetration of the technologies. However, the growth rates are exogenously specified. Thus, there is interest in providing the models with endogenous mechanisms that allow reproducing the typical patterns of the market penetration of the technologies (which for many technologies it has been empirically observed that follows a logistic curve, Grübler, 1991), instead of imposing them exogenously. Recent experiences reported by Grübler and Gritsevskiy (1997) have shown that the combination of learning curves and persistent uncertainty, two basic mechanisms at the core of the technological change dynamics, drive to logistic-like penetration patterns and consistent diffusion times. This is, in fact, a very interesting result, as the model is able to generate such patterns endogenously. It should be taken into account, for instance, for future developments in the ERIS or MARKAL models.

This is an example of the typical “lock-in” effect driven by the underlying increasing returns mechanism. A learning technology that has become competitive due to early investments will be installed more and more. Although this behaviour is not a problem in itself, as it helps to reflect the processes of technological "lock-in" of the real life, it also calls for a careful and consistent selection of growth constraints, maximum potentials and progress ratios for the learning technologies in the model.

The progress ratio, together with the maximum cumulative capacity, determines the ultimate specific cost that it is possible to reach. If this one is very low, and the market penetration constraints of a given technology permit sufficiently high values of capacity to be installed along the time horizon, possibly unrealistic cost reductions may be the result, which will on their turn drive to a further installation of capacity. Both maximum growth constraints and progress ratios control the learning possibilities of a given technology and, therefore, it is important to ensure a consistent definition, paying attention to their combined effect in the trajectory of a certain technology. Maximum growth constraints are advisable to control the penetration (that is, the learning over time) of the technology, but there is always a compromise as to what could be considered a “reasonable” combination of growth rates and progress ratio.

4.3.3 Sensitivity to the discount rate

The discount rate used in the computation of the total system cost has a strong influence in the technology choice of an energy optimisation model (Messner, 1997). Here, its effect on the MIP-learning model is illustrated.

The resulting generation mix under three different discount rates (5, 10 and 15%) is examined. Figure 29 presents the comparison of the electricity generation for the BaU scenario in the year 2050. Several changes are noticeable when the discount rate is modified. If the discount rate is increased to 10%, solar photo-voltaics, a technology with high initial investment costs but relatively low O&M costs that was competitive for the 5% discount rate case, is not introduced into the solution. On the other hand, the gas fuel cell, which did not appear previously and has lower investment costs but much higher O&M costs, comes in. With a further increase to 15%, none of those technologies appear. In addition, when the discount rate is increased, conventional coal plants and simple cycle turbines increase their output, while advanced coal plants and gas combined cycles decrease their production.

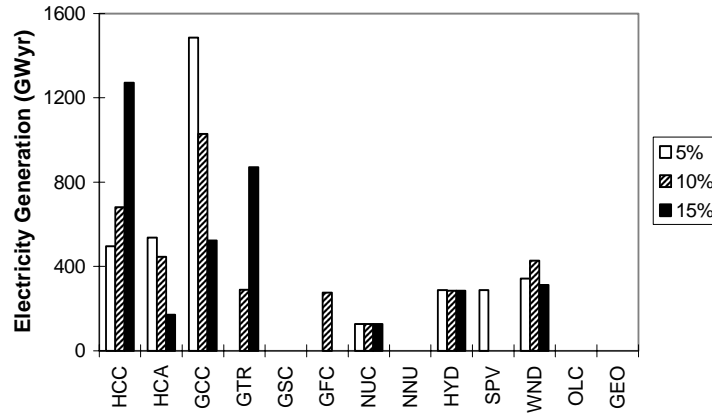


Figure 29. Electricity generation mix in 2050. BaU scenario. Different discount rates.

Under the stabilisation scenario, changes are less dramatic for the learning technologies, as low carbon technologies are forced into the solution due to the CO₂ constraint. However, also in this case, the model increases the generation of simple cycle gas turbines, at expense of the combined cycle gas turbine.

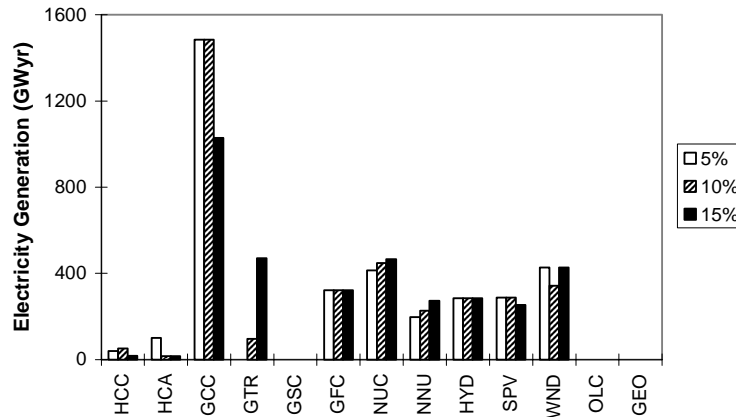


Figure 30. Electricity generation mix in 2050. Stabilisation scenario. Different discount rates.

Thus, a higher discount rate favours technologies with lower up-front investment costs, even if the operating costs are higher. As a consequence, emerging revolutionary technologies, whose investment costs are still high, may not be chosen under a high discount rate, such that the one that may be applied by private actors in liberalised markets. As those new technologies could very likely be cleaner and more efficient, this will have an impact on the emission profiles. The corresponding effects of the discount rate variation on the emission profiles in the BaU scenario may be appreciated in Figure 31.

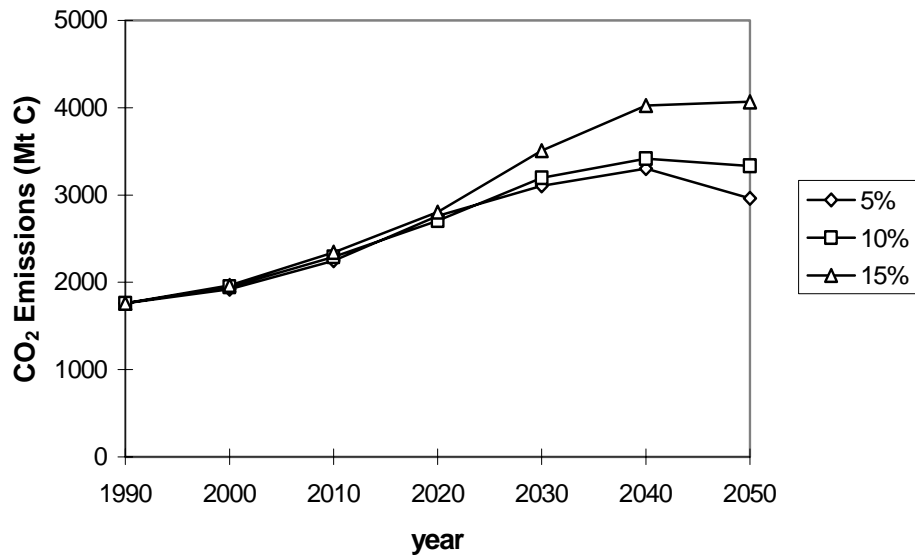


Figure 31. *CO₂ emissions from the global electric system. BaU scenario. MIP-Learning. Different discount rates.*

4.3.4 Learning curves with several progress ratios

It is interesting to analyse which learning conditions will allow or prevent the entrance of a specific technology into the marketplace and which may be the effects of speeding up/slowing down the learning process at further stages of evolution of a certain technology. Will the model still find a given technology attractive despite future changes of the learning process?.

A technology may present different learning speeds along different stages of its life cycle. This is a phenomenon already observed for the gas turbines. They had a faster learning in the R&D and demonstration phase, but it slowed down once the technology went to the competitive phase (MacGregor, 1991). One could specify different progress ratios for different ranges of cumulative capacity. Using this approach the change of learning rates can be handled. However, a threshold capacity (C_{thres}), from which the learning speed increases or decreases, has to be defined and the difficulty remains how to establish such value. A test of this procedure using arbitrary values is performed here.

The test is applied to the solar PV technology for which two progress ratios are considered. For this exercise, an arbitrary cumulative capacity threshold value of 100 GW has been used. Figure 32 presents the comparison of the specific cost curves with the two different progress ratios and the two-stage curve. Figure 33 presents the corresponding comparison between the cumulative cost curves.

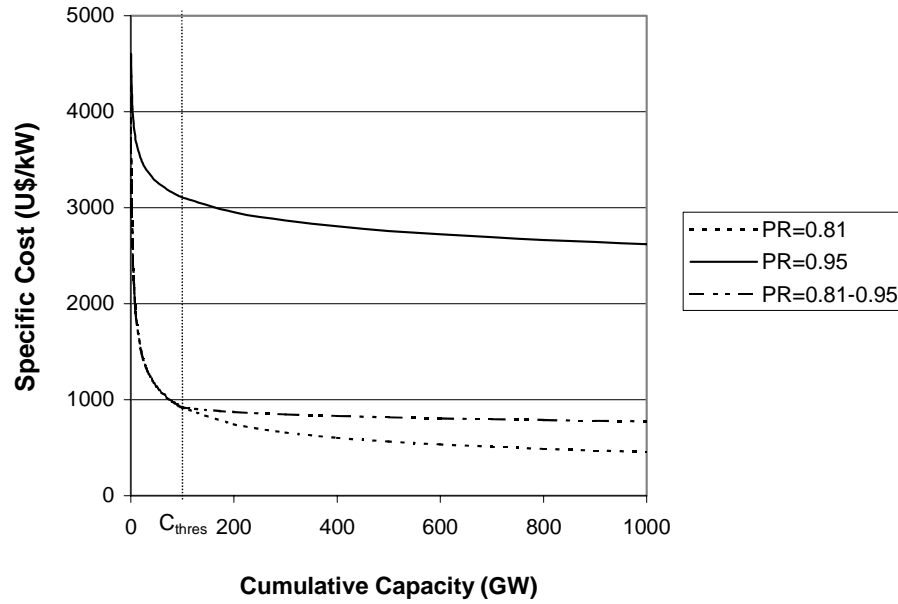


Figure 32. *The two learning-rates specific cost curve for solar PV.*

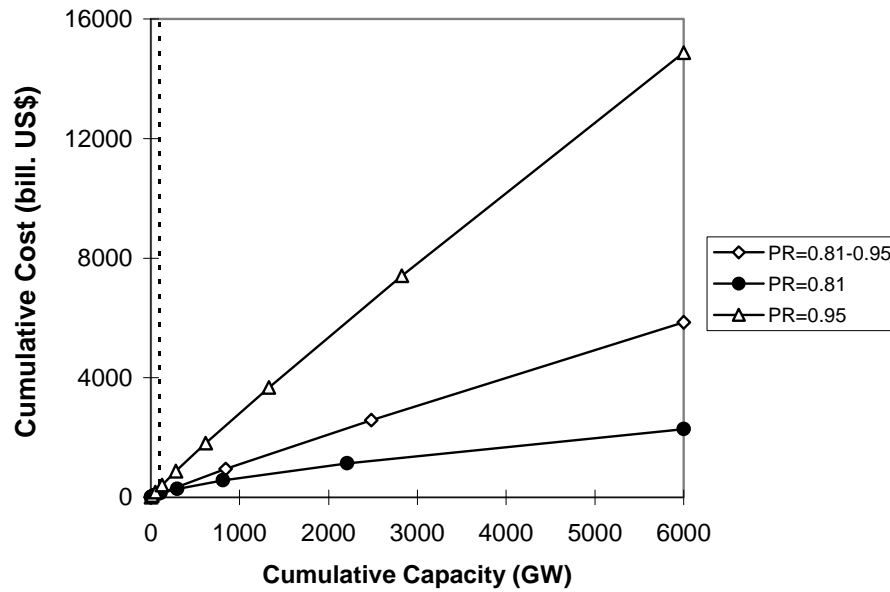


Figure 33. *The two learning rates cumulative cost curve for solar PV.*

With the introduction of a new learning rate, the segmentation of the whole curve is altered because the maximum cumulative capacity associated with the first progress ratio is not anymore the absolute maximum cumulative capacity $C_{k,max}$ but the threshold capacity C_{thres} . For the second progress ratio, C_{thres} is now the initial cumulative capacity. In this case, eight segments have been specified for the whole curve: Five segments for the first part of the

curve and three for the second one. For each part, the variable length segmentation rule described in numeral 3.6 has been applied. Of course, alternative segmentation procedures for a two-stage learning curve may be defined.

Notice that in this example with the original curve (PR=0.81) and the parameters used in this analysis the investment cost for the gas fuel cell technology may go down to 350 US\$/kW. The combination of two progress ratios provides a minimum specific cost of 970 US\$/kW.

Figure 34 presents the comparison of the electricity generation mix obtained with a single progress ratio (PR=0.81, already presented above) and two progress ratios in the BaU scenario (results for the stabilisation scenario were not affected by this change). In the two-stage learning case, the solar PV technology is not cost competitive for the reference conditions, and, consequently, the generation with advanced coal plants and wind turbines is higher than in the one-stage case.

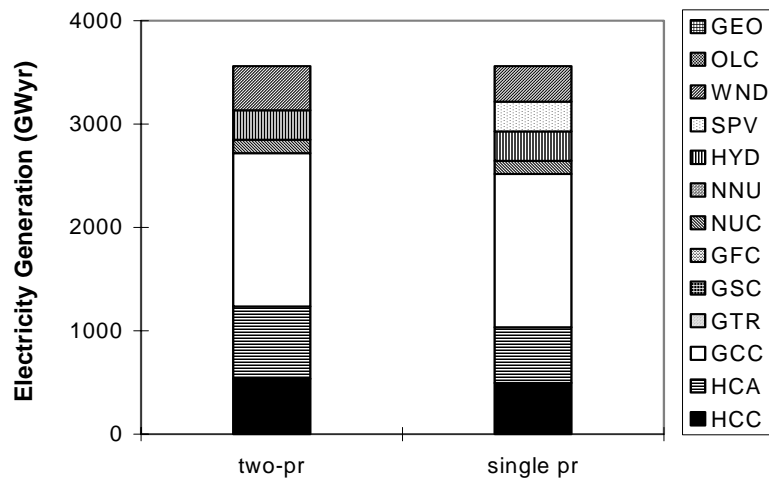


Figure 34. Comparison of generation mix in 2050 - One Vs Two progress ratio- BaU scenario

It could be useful to use several progress ratios when unrealistic cost reductions have to be avoided. The cost reduction could be controlled using a two-stage learning model. As already illustrated above, under the particular conditions of our analysis and with the progress ratio values been used up to now, some of the technologies may go to fairly low investment costs. A two-stage learning model may be a useful alternative to specify realistic limits of the cost reduction, without imposing a fixed lower bound ("floor" cost) that rules out the possibility of further learning for a particular technology after a given threshold.

5. A post-Kyoto analysis with the ERIS model prototype

Here, using a multi-regional version of the ERIS model prototype incorporating endogenous technological learning, a simplified analysis of the global electricity generation system has been performed. The results presented here are drawn mainly from Barreto and Kypreos (1999a) and Barreto and Kypreos (2000a). The main purpose of this analysis is to provide a general picture of the long-term evolution of the global generation mix, examining the possible effects of Kyoto-like CO₂ constraints when technological learning is present. In addition, using a two-stage programming approach, some stochastic analyses are performed to examine the effect of uncertainties in the CO₂ reduction targets, demand and learning rates. Also, a preliminary analysis of the effects of the geographical scale of learning is included.

The same technological parameters and learning curves described in numeral 4.1 are used. A generic specification of generation technologies has been introduced across the different regions. That is, besides installed capacities, availability factors and potentials for renewable technologies, no regional specification of costs or technical characteristics is carried out. However, for solar PV and gas fuel cell, an explicit "floor" specific investment cost of US\$ 500/kW is provided. This represents a "cutting-off" on the learning process, but it is incorporated in order to avoid unrealistic cost reductions.

5.1 Regionalisation

For this analysis, the regionalisation of ERIS has been chosen following that of the MERGE3 Model (Manne and Richards, 1997). That is, nine geopolitical world regions have been considered. Four regions represent the industrialised countries: United States (USA), Western Europe (OECD), Canada, Australia and New Zealand (CANZ) and Japan (JAPAN). One region represents the economies-in-transition: Eastern Europe&Former Soviet Union (EEFSU). Together, the five regions conform the Annex I group. Four additional regions group together the developing countries: China (CHINA), India (INDIA), Mexico and OPEC (MOPEC) and the Rest of the World (ROW). This regionalisation suffices for the purposes of our generalised analysis, but more detailed studies could require a different definition of the regions according to different criteria (e.g. similarities in their electricity markets, geographical, etc.). In this indicative analysis, no attempt was made to conceive a new regionalisation and the results will be presented mainly at an aggregated global level. Also, learning is assumed to occur at the global scale. That is, all regions contribute to the cost reduction.

5.2 Electricity demand

The demand corresponds to the REFXII/A2 scenario resulting from the combination of the REFXII scenario from the POLES model (Criqui, 1999) and the A2 scenario from IIASA-WEC (1998). It is therefore a high growth scenario and should not be regarded as a "reference" scenario in the usual sense. In this projection, global electricity demand grows at an average of almost 3% per year between 2000 and 2050. Annex I countries account for 43% of the worldwide electricity demand by the year 2050. Figure 35 presents the regional demands and Figure 36 provides a comparison of the aggregated global demand with the electricity generation of the IIASA-WEC (1998) A2 scenario.

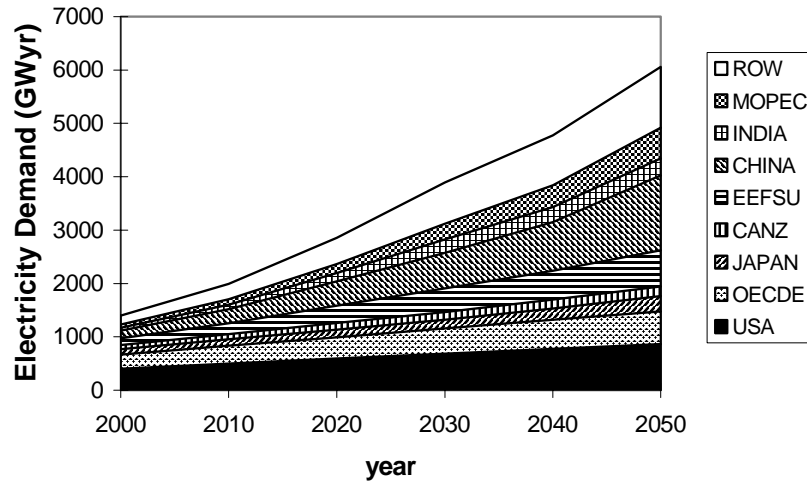


Figure 35. *REFII/A2 electricity demand scenario.*

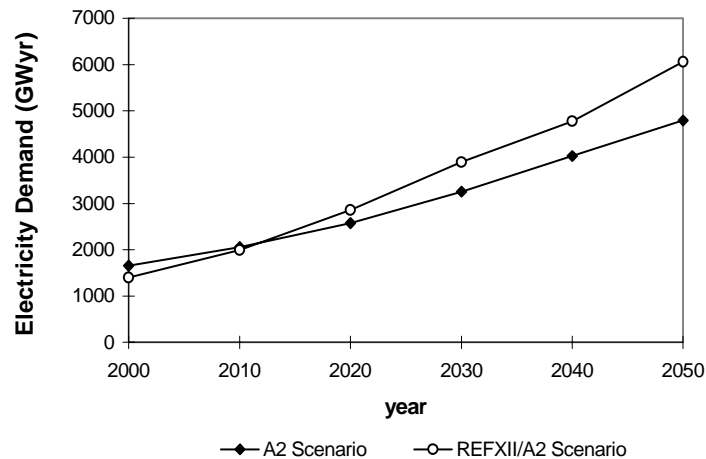


Figure 36. *Comparison between TEEM REFII/A2 and IIASA-WEC A2 scenarios.*

5.3 Definition of CO₂ emission scenarios

Regarding CO₂ emissions three basic scenarios have been considered. The first one examines an unconstrained situation (Business as Usual, BaU). The second one imposes a constraint on CO₂ emissions on the Annex I regions, assuming that their electricity systems are compelled to achieve the Kyoto-agreed percentage reduction from the 1990 levels by the year 2010 and keep these levels constant for the rest of the horizon (Kyoto-for-ever).

For the fulfilment of the Kyoto-for-ever target, three different variants have been considered. In the first one, the emission targets must be fulfilled in each Annex I region. That is, no trade of emission permits is allowed. In the second one, trade is allowed among the Annex I regions. In the third variant the influence of allowing emissions trade across all regions is examined, extending the trade to non-Annex I regions after the year 2030. In order to avoid carbon leakage, in the constrained scenarios non-Annex I regions are bounded to their BaU baseline emissions.

As a complement an additional CO₂ constrained scenario is analysed, where both Annex I and non-Annex I regions face emission reduction commitments (Kyoto global trend scenario). In this scenario Annex I countries follow a "Kyoto trend" constraint, with a linear extrapolation from the target for the year 2010 (5% per decade until 2050). The non-Annex I countries face an arbitrary linearly decreasing CO₂ target imposed for the period 2030-2050 (5% per decade after 2030). Trade across all regions is allowed after 2030.

It should be noticed here that, although the attention has been concentrated in CO₂ emissions, other pollutants such as SO₂ or NO_x, related to regional and local pollution problems, will also play an important role in the selection of generation options around the world.

5.4 Some results

5.4.1 Unconstrained scenario (BaU)

Figure 37 presents the evolution of the global generation mix for the CO₂ unconstrained (BaU) scenario, under the above described assumptions. A clear dominance of coal plants is evident in the satisfaction of the rapidly increasing demand. Although mainly conventional units are installed, advanced coal power plants are also introduced. However, gas combined cycle plants experience a very significant growth becoming the dominant technology by the end of the horizon. Oil-fired generation is practically phased out and nuclear keeps a small share. Wind turbines, already an economic alternative in several markets, are introduced along their maximum penetration constraint. Gas fuel cells also undergo a certain growth, though their participation remains modest. Under these circumstances solar photo-voltaics is not economic and is not introduced.

Figure 38 presents the regionalised evolution of CO₂ emissions from electricity generation in this scenario. A substantial increase occurs along the time horizon. Developing regions, with fast growing electricity markets relying upon indigenous fossil fuel resources (mainly coal) to meet the demand, become important contributors to the global CO₂ emissions in the long term.

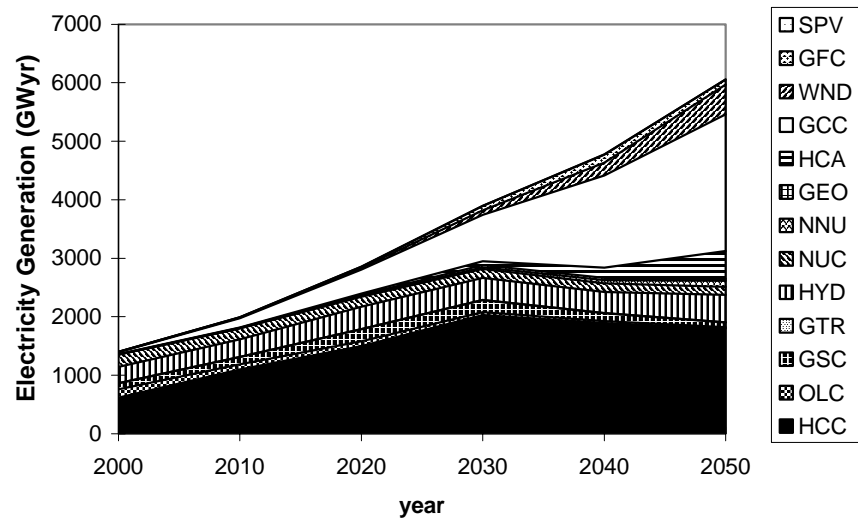


Figure 37. *Global electricity generation. BaU scenario.*

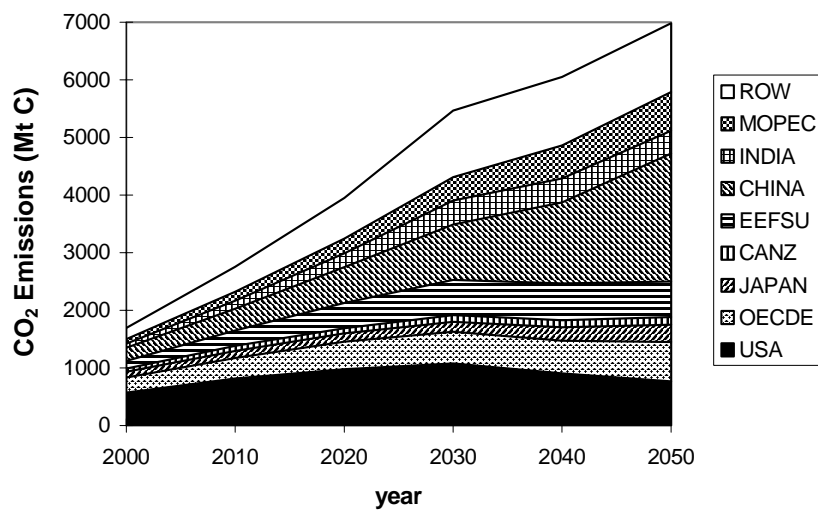


Figure 38. *CO₂ emissions from the global electricity system. BaU scenario.*

5.4.2 Kyoto-for-ever scenario

In this section the behaviour of the system under the Kyoto-for-ever target is examined under different assumptions concerning trade of emission permits.

5.4.2.1 No trade

In first place, the fulfillment of the Kyoto-for-ever target without allowing trade among the regions is examined. Figure 39 presents the electricity generation mix and the corresponding CO₂ emissions are presented in Figure 40.

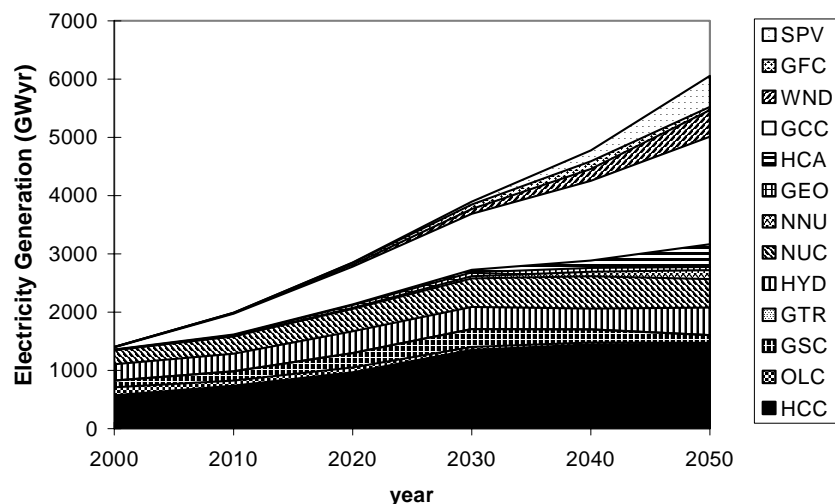


Figure 39. *Global electricity generation. Kyoto-for-ever scenario. No trade.*

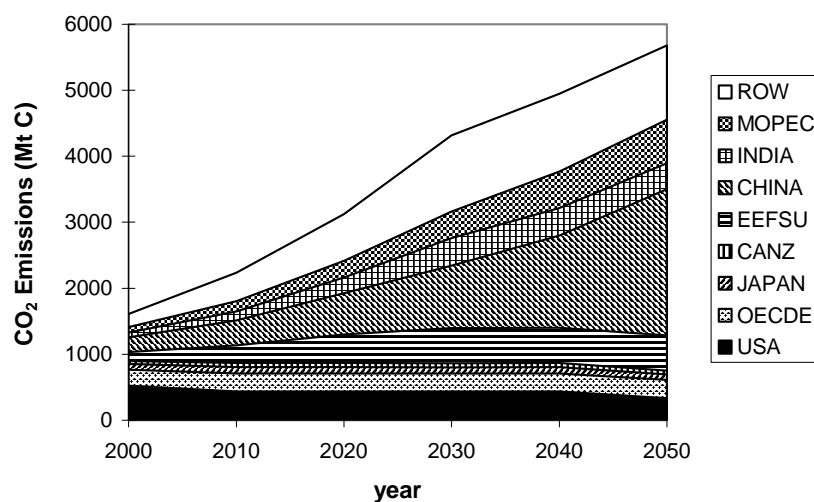


Figure 40. *CO₂ emissions per region. Kyoto-for-ever scenario. No trade.*

The constraints imposed in the Kyoto-for-ever scenario provide an opportunity for the introduction of less carbon-intensive or carbon-free technologies in the regions with reduction commitments. This situation implies a significant departure from the coal intensive trajectory the system was following in the previous unconstrained scenario. Coal, however, still continues to be an important primary fuel in the electricity supply through both conventional and clean coal technologies. In particular, some of the non-constrained regions continue to rely heavily on it (CHINA and INDIA). Nuclear (both conventional and new) plants experience a significant growth. Gas fuel cell is introduced to a minor extent, lower than in the BaU case. Despite the fact that Annex I countries achieve long-term stabilization of their CO₂ emissions, global emissions still experience a substantial increase.

Under this scenario, solar PV becomes an attractive technology penetrating to a large extent in Annex I regions but also, though to a smaller extent, in non-Annex I regions (see Figure 48 and Figure 49 below for a comparison of the generation mix for the year

2050, in Annex I and non Annex I groups, for the three trade variants considered). In this situation, the technological learning stimulated by the constraint is sufficient to bring the costs of solar PV to competitive levels, being deployed in both groups. It is important here to notice how the representation of endogenous learning influences such outcome. As global spill-over of learning has been assumed, cumulative capacities are added up across all regions in order to compute the resulting investment costs for the learning technologies. Therefore, installation of a certain technology in one region will affect the uniquely defined investment cost and can certainly make this technology economic in another region. A simple sensitivity to the geographical scale of learning is presented in the section 5.6.

5.4.2.2 Trade among Annex I regions

In this case, trade is allowed among the Annex I regions. The possibility of trading emission credits allows some Annex I regions to follow more moderate changes in the structure of their electricity generation systems. However, while output from gas combined cycle plants increases, generation from conventional coal plants remains low, well under the BaU levels. The generation mix of the non-Annex I group remains essentially unaltered, with the exception of solar PV, which reduces its share in both Annex I and non-Annex I countries when compared to the no trade situation. Here, the global spill-over of the learning process also plays a role. As lower investments on solar PV are carried out in the Annex I group, smaller cost reductions are experienced and, therefore, lower installations also occur in the non-Annex I group. Besides the significant change in solar PV, the situation at the aggregated global level is not markedly different from that in the case without trade (see Figure 48 below).

As the emissions target for the EEFSU region exceeds by far the level of emissions, the EEFSU becomes the main seller of emission credits along the horizon. That is, the so-called "carbon bubble" created in the Former East Block due to the economic crisis, exerts a significant influence on the trade⁴⁵ and, therefore, in the fulfilment of the Kyoto-for-ever target. In fact, in this situation global emissions are slightly above than in the previous no trade variant.

5.4.2.3 Full trade

When emissions trade across all regions is allowed, a fraction of the abatement effort occur in some of the non-Annex I regions where output from gas combined cycle and conventional coal plants is reduced, while less carbon intensive options increment their production levels. In particular, a much higher penetration of solar PV than in the previously examined variants of the Kyoto-for-ever scenario is observed. The Annex I regions undertake a less radical decarbonisation in their generation mix, as they are allowed to fulfil part of their commitments by means of international cooperation mechanisms. In particular, less generation from nuclear, solar PV and hydro is observed in this group of countries, while coal and gas power plants increase their output. Gas fuel cells are introduced to a higher extent than in the previous cases, but they do not grow enough to gain a sizable share of the market.

⁴⁵ For a comprehensive analysis of the possible effects of the "carbon bubble" on the compliance of the Kyoto Protocol see, for instance, Victor et al. (1998). According to their analysis, Russia and Ukraine would be very likely the major contributors to sales of "bubble" permits.

The generation mix in the year 2050 in Annex I and non-Annex I countries under the Kyoto-for -ever constraint for the no trade, trade-in-Annex-I-regions and full trade situations is presented in Figure 41 and Figure 42.

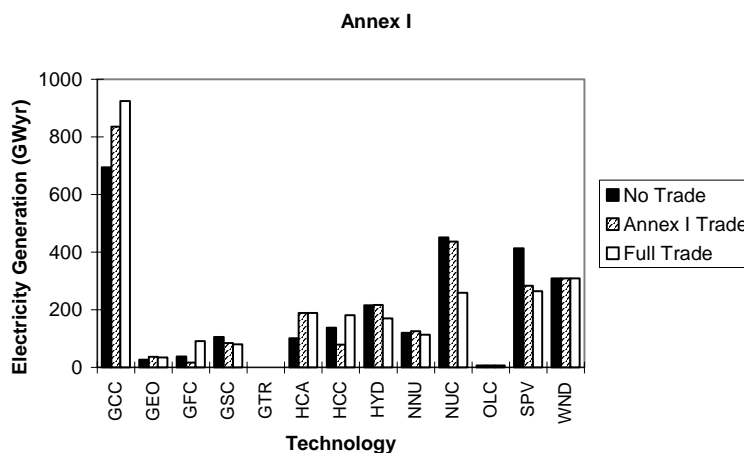


Figure 41. Electricity generation in the Annex I group in 2050. Kyoto-for-ever scenario.

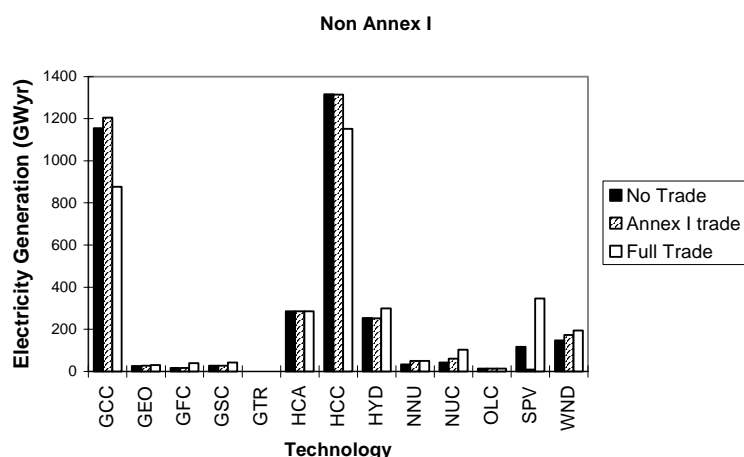


Figure 42. Electricity generation in the non-Annex I group in 2050. Kyoto-for-ever scenario.

It has to be mentioned that the possibility of trading emission permits, either within Annex I regions or together with non Annex I ones, does not imply that abatement measures are not undertaken inside the regions facing CO₂ mitigation commitments. Even more, when technological learning is endogenous, trade of emission permits may provide opportunities for introduction of learning technologies in different regions.

Figure 43 presents the CO₂ abatement costs for the different variants of the Kyoto-for-ever scenario. Abatement costs are defined here as the difference in total cumulative discounted system costs to the BaU scenario. For comparison, the abatement costs obtained for the same target and trade variant when technology costs are considered time-independent (Linear Programming static model) are also presented in the same figure. The benefits of trade and technological learning can be appreciated.

The results of the model under the Kyoto-for-ever scenario show that, when technology dynamics is endogenised, mitigation policies play an important role in inducing the technological development of clean technologies. Although the results presented here cannot be considered, by no means, exhaustive, this behaviour would indeed be in line with the claim that early action is required to induce and stimulate the necessary technological learning (Grubb, 1997, Grübler and Messner, 1998, Nakicenovic, 1997).

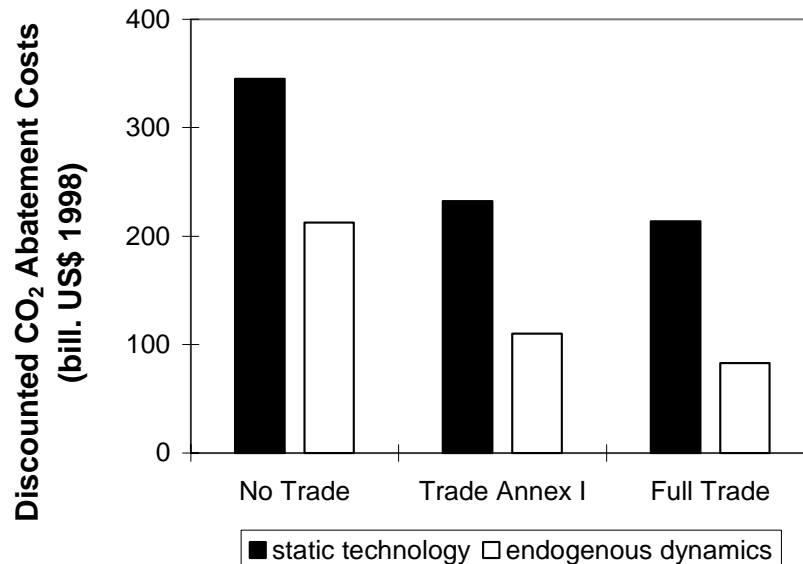


Figure 43. Comparison of discounted CO₂ abatement costs. Kyoto-for-ever scenario.

5.4.3 Kyoto global trend scenario

Here, the results for this scenario, where both Annex I and non-Annex I countries face CO₂ reduction targets and trade across all regions is allowed, are presented. It represents a more stringent reduction than the previous cases, as the non-Annex I countries that did not face any restriction in the previous scenarios (besides, of course, the bounds to avoid carbon leakage), must commit themselves to abatement actions.

The evolution of the global electricity generation for this scenario is presented in Figure 44 and the corresponding regionalised CO₂ emissions in Figure 45. Under this stronger reduction commitment, conventional coal power plants begin to be phased out after 2030 and advanced coal plants experience a much lower penetration than observed in the other situations. Higher amounts of solar photovoltaics and gas fuel cells (this one barely used in the Kyoto-for-ever case) are introduced to the system. Also, conventional nuclear production is increased. Gas combined cycles and hydro plants experience no significant variation in comparison to the previous cases.

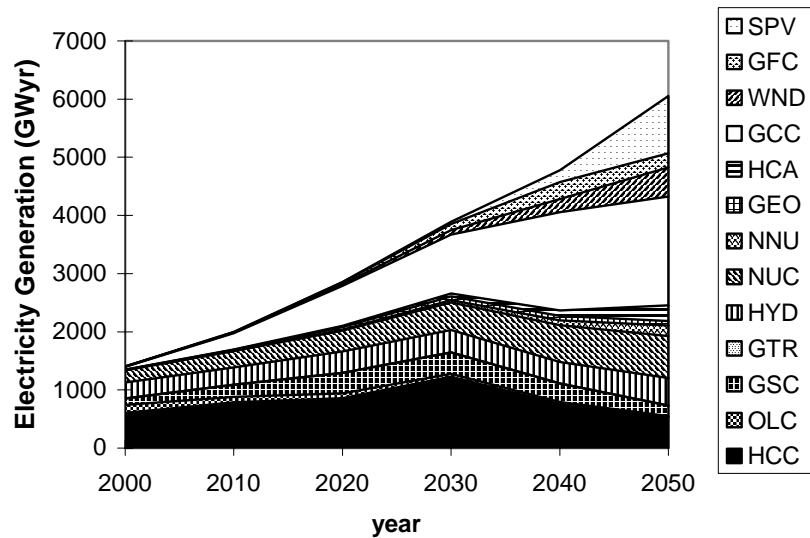


Figure 44. *Global electricity generation. Kyoto global trend scenario.*

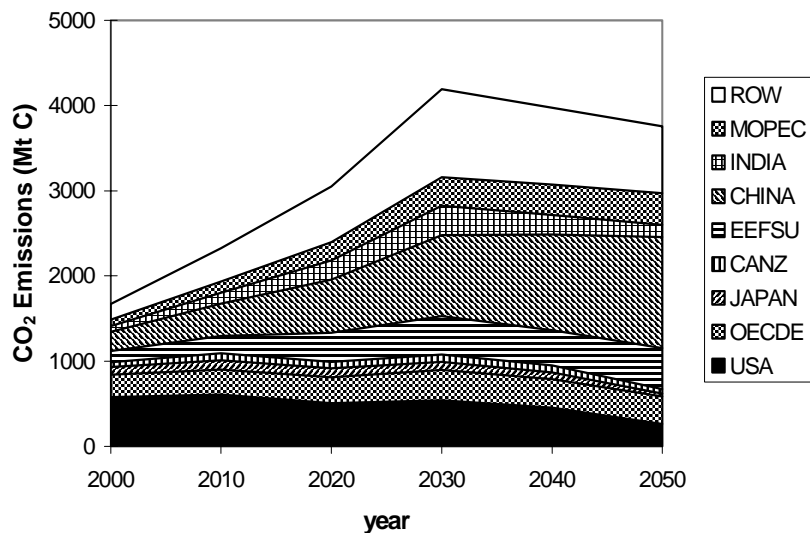


Figure 45. *CO₂ emissions from the global electricity system. Kyoto global trend scenario.*

Figure 46 and Figure 47 present a comparison of the electricity generation per technology in Annex I and non-Annex I countries for the year 2050 under three different CO₂ scenarios. Important structural changes of the generation mix are noticeable as the emission constraints become more stringent. Several emerging technologies such as solar photo-voltaics, wind turbines and gas fuel cells experience a very significant growth in both the developing and developed countries. Nonetheless, the gas combined cycle plant continues to be the dominant technology in both groups. Conventional coal generation is significantly reduced, and the bulk of the remaining coal electricity production in this scenario is carried out in the developing countries.

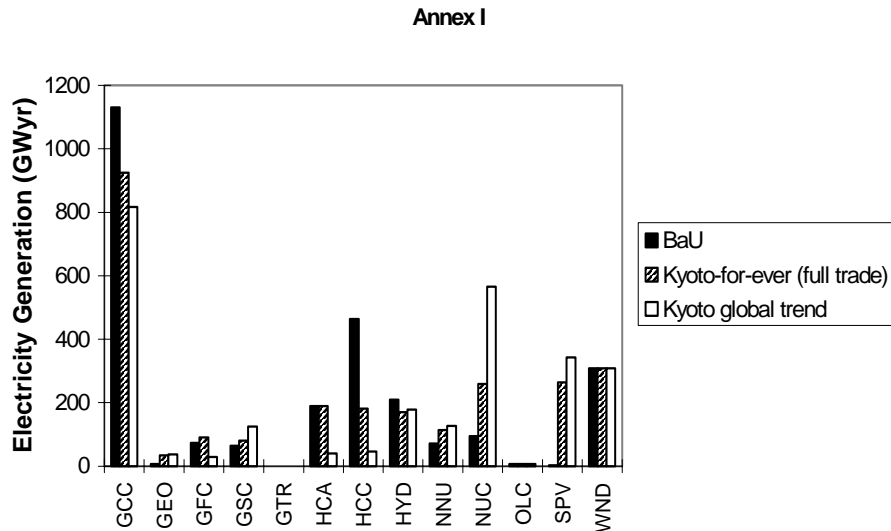


Figure 46. Comparison of electricity generation mix in 2050. Annex I group. BaU, Kyoto-for-ever(full trade) and Kyoto global trend scenarios.

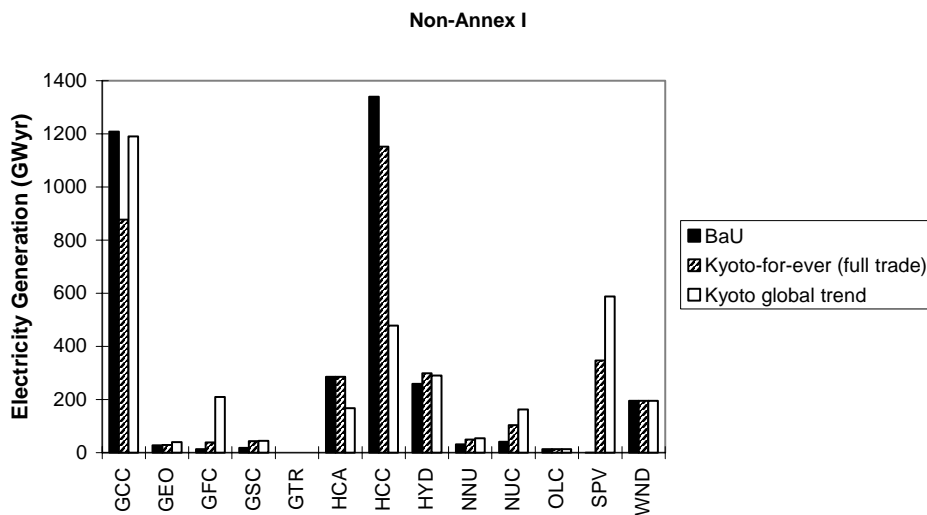


Figure 47. Electricity generation mix in 2050. Non-annex I group. BaU, Kyoto-for-ever (full trade) and Kyoto global trend scenarios.

As a comparison, Figure 48 depicts the global electricity generation mix in the year 2050 for the different scenarios and cases. Figure 49 presents the comparison of the regional CO₂ emissions for the same year and cases and Figure 50 the global evolution of emissions along the time horizon. Among the Kyoto-for-ever constrained cases, the trade in Annex I variant exhibits the highest global emissions. Emissions in the Kyoto global trend scenario are significantly lower than those in BaU, as this constraint demands important abatement actions from developed and developing countries alike. In particular, for some developing regions such as CHINA, this commitment implies a strong reduction.

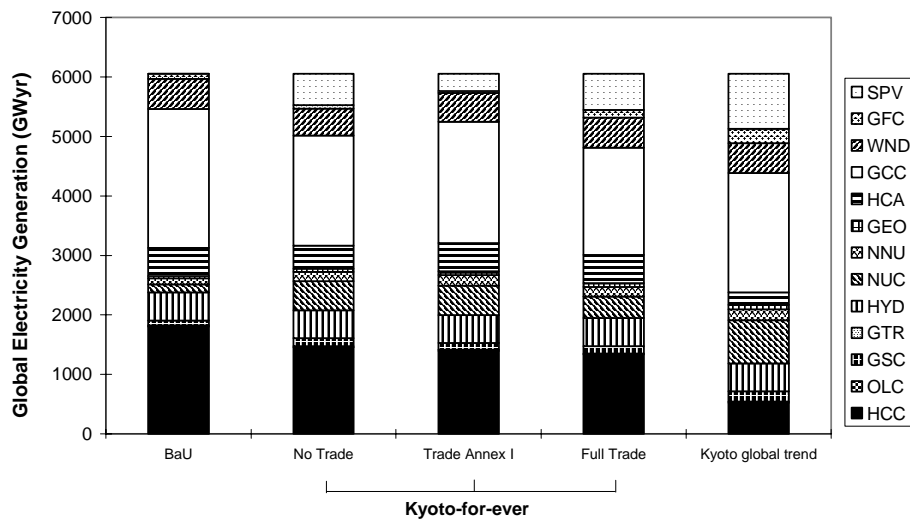


Figure 48. *Global electricity mix in 2050. BaU, Kyoto-for-ever and Kyoto global trend scenarios.*

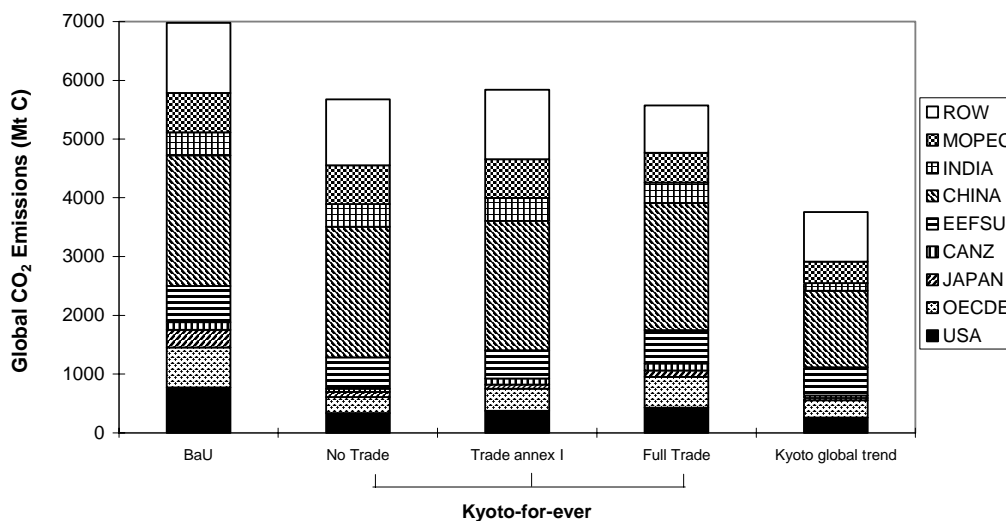


Figure 49. *Regionalised CO₂ emissions in 2050. BaU, Kyoto-for-ever and Kyoto global trend scenarios.*

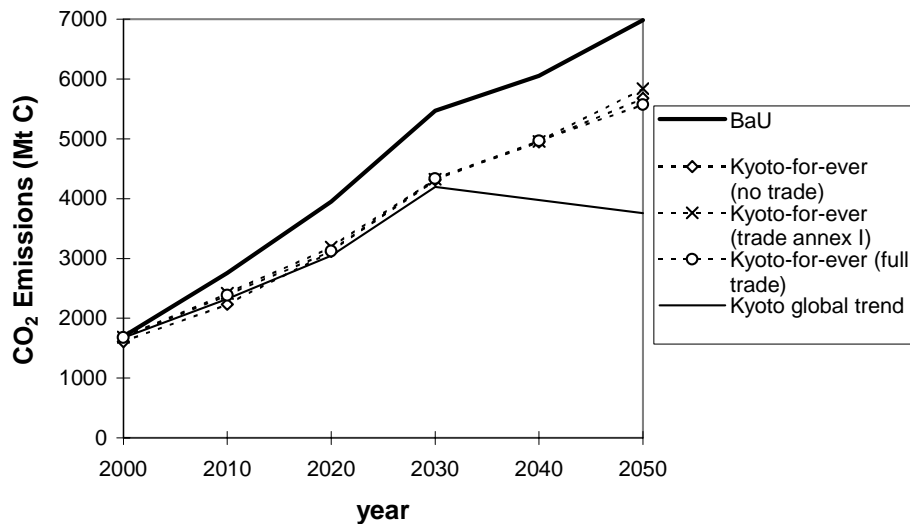


Figure 50. Comparison of global CO₂ emission trajectories. BaU, Kyoto-for-ever and Kyoto global trend scenarios.

5.5 Stochastic analyses

Some stochastic analyses have been performed to examine the influence of uncertainty in CO₂ constraints, demand growth and learning rates in the evolution of the system. In each analysis only one of these parameters is considered uncertain and uncertainty is assumed to be resolved in time (in the year 2030) for all of them. As a simplifying assumption, unless specified otherwise, all states of the world are considered with equal probability of occurrence.

5.5.1 Stochastic CO₂ constraint

For the analysis of uncertainty on the mitigation targets the system may face, two states of the world are considered: unconstrained CO₂ emissions and Kyoto-for-ever (without trade) commitments. Figure 51 presents the evolution of the global carbon intensity for electricity generation (ton C/kWyr) as an outcome of the stochastic analysis and compared to the previously described deterministic cases. In the stochastic situation, during the first stage the electricity generation system basically follows the same decarbonisation path of the deterministic Kyoto-for-ever target. Capacity is built up in low-carbon or carbon-free technologies, mainly solar PV and conventional nuclear, but also, although to a lower extent new nuclear and gas fuel cells. Figure 52 presents a comparison of the corresponding generation mix obtained for the year 2050.

The early investments induced by the first stage emissions reduction results in cost reductions and market penetration of several emerging learning technologies. This drives to much lower carbon intensity, as compared to the deterministic BaU trajectory, even in the unconstrained state of nature (BaU-Sto), which is progressively less affected in the second stage. As illustrated with these results, uncertainty in emission reduction commitments drives to early action as a preparation for future contingencies. When technological learning is endogenous, the investments induced by this hedging policy

will contribute to the required technological progress, possibly making more intense mitigation actions in the long term less expensive.

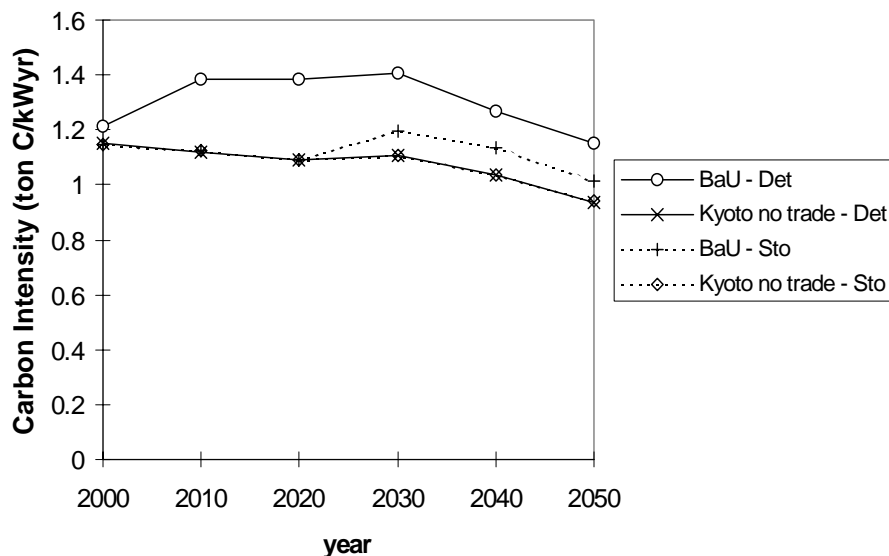


Figure 51. Carbon intensity of global electricity generation. Stochastic analysis.

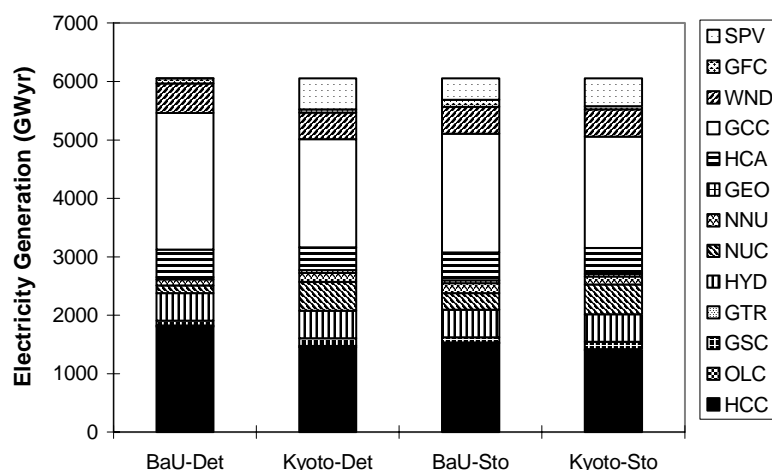


Figure 52. Comparison of generation mix in 2050. Stochastic Vs deterministic cases.

5.5.2 Stochastic demand growth

Future trends of the demand are highly uncertain and will affect technology choice, resource consumption and resulting emissions in the global electricity system. In order to examine the impact of uncertain demand growth rates, two states of the world are considered here. The first one considers the electricity demand examined so far, and a second state is specified with a lower demand (-15% from 2010). Figure 53 presents, for the year 2020, the last period before the uncertainty resolution, the electricity generation for five of the six learning technologies (gas combined-cycle is excluded because it is not an emerging technology and the magnitude of its generation does not fit into the

scale for comparison) in the stochastic case as compared to the corresponding deterministic high and low demand scenarios for the Kyoto-for-ever CO₂ constraint (no trade). The possibility of a higher demand provides opportunities for higher growth in some technologies. In this particular case early learning of some lower-carbon technologies is also favoured. This occurs in the high-demand deterministic case but it is also reflected in the stochastic one, where solar photo-voltaics and gas fuel cell experience a higher growth than they do in the low demand deterministic case. The early investments in low-carbon, more efficient technologies carried out in the first stage, stimulated by the possibility of a higher demand, result in a different (lower) emission trajectory in the second stage for the low demand state-of-the-world (see Figure 54).

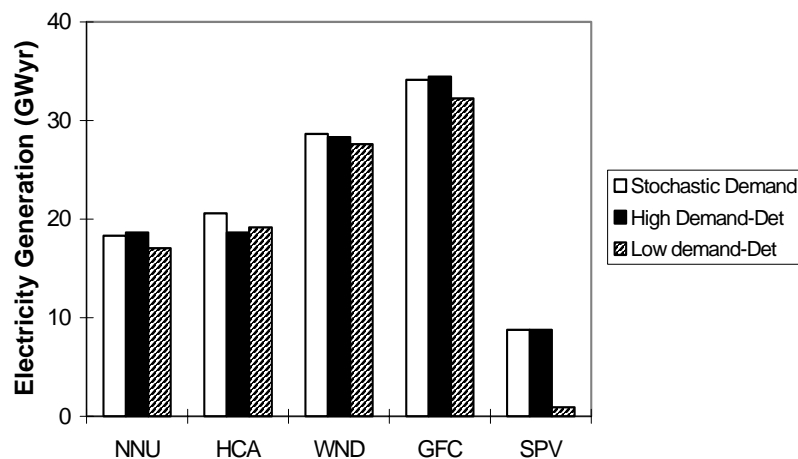


Figure 53. Electricity generation from learning technologies in 2020. Stochastic Vs deterministic demand. Kyoto for ever scenario (no trade).

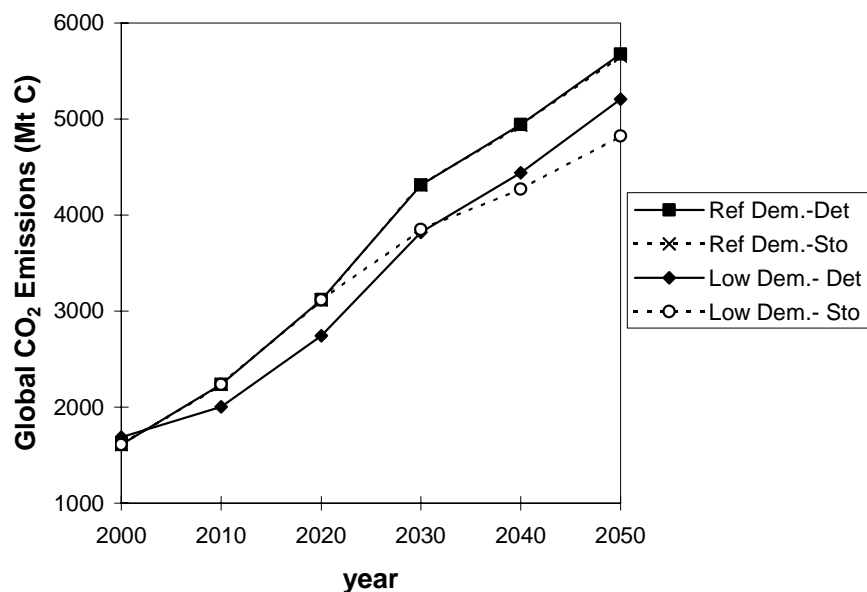


Figure 54. Comparison of global emissions for the Kyoto for ever scenario (no trade). Stochastic Vs deterministic demand.

5.5.3 Stochastic progress ratio

Uncertainty is inherent to processes of technological change. The technological competition takes place in an uncertain selection environment where market conditions, environmental constraints, institutional and social structures, R&D results, user preferences etc. are continuously evolving. The conjugate effect of many interacting factors may drive some technologies to experience an extensive diffusion, while many others fail to further develop and penetrate. The “winners” and their characteristics, however, are not known *ex-ante*, and at early stages of technology development it is usual to have several competing innovations (Grübler, 1996). Very likely, only a few of these alternatives will be chosen by the system. Neither the ultimate characteristics and impacts nor the evolution of costs and performance along the life cycle can be foreseen when an emerging technology is introduced.

The progress ratio constitutes one of the fundamental and most sensitive assumptions when technological learning is endogenised. However, there is significant uncertainty regarding the future values this parameter may exhibit. A number of not easily predictable factors intervene in the learning or "forgetting" processes that will drive to the progress or stagnation of a given technology. It is possible that a slowdown or a further acceleration of learning occur as the technology proceeds from its infancy to its maturity (Ayres and Mártinas, 1992, Grübler et al., 1999).

Although historical data may provide valuable information about past learning trends, it is not possible to foresee if the observed trends will continue in the future or new developments will cause an alteration of the learning trajectory. The extrapolation of initial trends could drive to an overestimation or underestimation of the learning rates. Also, even historical estimates can be uncertain, providing different values depending on the data sets, time span and performance indicators used (Schrattenholzer, 1998a, Neij, 1999a).

Therefore, the introduction of an analytical framework to handle the uncertainty associated to technological learning is a necessary step to its further understanding and adequate representation. Different approaches have been followed in the literature. Grübler and Gritsevskiy (1997) apply a micro-model following a complex stochastic programming approach, where uncertainty is persistent along the time horizon and a probability distribution is specified for the learning rates. Using this probability distribution, stochastic samples are drawn and integrated into an overall objective function⁴⁶.

Mattson (1998) uses a pre-specified cumulative capacity threshold to resolve the uncertainty (instead of a given time period), on the rationale that information about the learning rates is obtained only if actual investments take place. This alternative drives to a multi-stage problem where uncertainty is resolved independently for each technology.

⁴⁶ Gritsevskiy and Nakicenovic (2000) applied the same approach to handle uncertainty in learning rates and costs in a single-region large-scale model, but the solution required very large computation power.

Here the influence of progress ratio is examined using a more traditional two-stage stochastic approach⁴⁷, with uncertainty resolution occurring at a pre-specified time. Nonetheless, it would be interesting to explore further the two alternative approaches mentioned above in order to establish whether they can be implemented in ERIS or MARKAL.

The analysis is carried out for a single technology, solar photo-voltaics. Up to this point in the analysis a progress ratio of 0.81 has been considered for such technology. Being an emerging technology, solar PV very likely has ample room for improvements. However, the potential for cost reduction is still uncertain. Consequently, three states of the world are considered. Solar PV may assume either a PR=0.72, PR=0.81 or PR=0.90⁴⁸. The evolution of the corresponding cumulative capacity over time is used to compare the stochastic outcome with the deterministic cases. Figure 55 presents the comparison of the cumulative capacity of solar PV under the Kyoto-for-ever scenario (full trade), between the deterministic and the stochastic cases. The values are expressed in relative, and not absolute, terms. Cumulative installations for the deterministic case with PR=0.81 have been chosen as the reference (i.e. 100%).

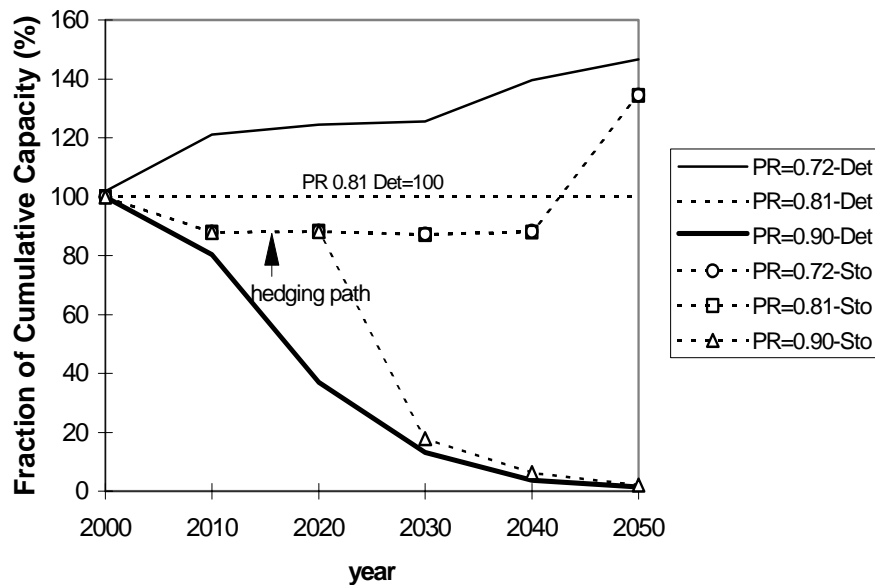


Figure 55. Cumulative capacity relative to the deterministic PR=0.81 case. Kyoto-for-ever scenario (full trade). Stochastic Vs deterministic cases.

The deterministic case with PR=0.72 presents, as expected, a higher level of early investments. Obviously, if the technology were able to follow a steeper learning curve, competitive investment costs will be reached earlier. On the other hand, the deterministic case with PR=0.90 results in a much more reduced growth of the technology. The progress ratio is not attractive enough to bring significant investments

⁴⁷ The approach was implemented in ERIS following the work of Van Geffen (1995) for a reduced version of the MARKAL model.

⁴⁸ Although the progress ratio values are very different, the effect of this difference is somewhat reduced because the curves must converge to the same specific "floor" cost mentioned above. This reduces to some extent the expected benefits of PR=0.72. The curve with PR=0.90, however, is always well above the "floor" cost.

in and the technology remains marginal. In the stochastic case, under the presence of uncertainty in the progress ratio, the model tends to follow an intermediate hedging path in the first stage, driving to a more gradual diffusion of the technology than that observed for the PR=0.81 and PR=0.72 deterministic cases, but avoiding the "lock-out" occurring in the case PR=0.90. Thus, as possibilities for high learning exist, in the stochastic case the model gradually builds up a certain amount of capacity that will allow further growth and development of the technology in case it is required⁴⁹. That is, the model lets a critical amount of technological learning to take place in order to be prepared for further developments.

The results reveal the importance of introducing a stochastic treatment for the learning rates. Deterministic scenarios will not introduce learning technologies without sufficiently attractive learning rates, and will instead try to get the maximum of those technologies with the lowest progress ratios. The learning rate of a certain technology is, however, uncertain, particularly for emerging (or future) technologies. The stochastic approach seems to follow a more balanced approach, diversifying the technology choice and favouring the installation of certain amounts of different technologies in order to hedge against their uncertain learning rates⁵⁰.

Nevertheless, the results are significantly sensitive to the probabilities of occurrence of the different states of the world. Changes in the relative weights may make a particular state of the world predominant and the response of the model to those changes will not necessarily be "smooth" (see Appendix 3 below for an illustrative example). To illustrate the effect of the assigned probabilities, Figure 56 presents the results when the probability of PR=0.72 is augmented to 0.40. The probabilities of the two other states are still considered equal and adjusted to 0.30 each. In this case, having the "optimistic" state a higher weight, the capacity installations during the first stage are higher, being now the growth of the technology above that of the reference (PR=0.81) deterministic case.

⁴⁹ The stochastic case increases the size of the model considerably (14352 constraints, 8932 variables) as compared to the deterministic one (5328 constraints, 3356 variables). The solution is much more difficult and solution times are, correspondingly, significantly higher (90 Vs 17 minutes in a Pentium PC 300 MHz for one of our typical cases).

⁵⁰ Analyses with energy optimisation "bottom-up" models incorporating uncertainty but not endogenous learning also show a tendency to diversification of the technology choice (Messner et al., 1996, Fragnière and Haurie, 1995). However, in the absence of learning, the diversification does not include radical technologies. The choice of hedging technologies remains in the "technological neighbourhood" (Grübler and Gritsevskiy, 1997).

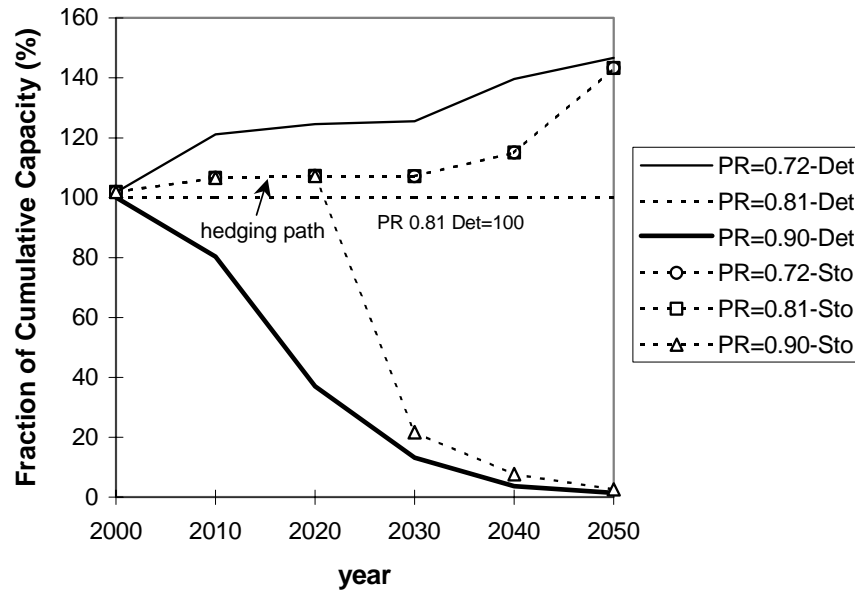


Figure 56. Cumulative capacity relative to the deterministic $PR=0.81$ case. Kyoto for ever scenario (full trade). Stochastic Vs deterministic cases. Probability $PR=0.72$ changed to 0.40.

5.6 Global Vs regional learning

As a first attempt to analyse the consequences of cooperative versus non-cooperative learning, a sensitivity exercise has been carried out considering that different regions may learn separately (though it is assumed that they follow the same learning curve). That is, accumulation of experience in one region does not influence cost reductions in other(s). Here, two arbitrarily chosen learning groups have been considered: Annex I and non-Annex I countries. That is, each Annex I region profits fully from cost reductions caused by capacity accumulated within its group, but cannot do so from the capacity accumulated in the non-Annex I group, and vice versa.

It must be noticed that this separation is performed here only with illustrative purposes. In reality, although a regional differentiation on the learning is plausible, the dynamics of learning processes at international level are highly complex and the intervening regions cannot be easily determined.

The cases where learning is global and where Annex I and non-Annex I groups learn separately are compared. The exercise should be regarded as an indicative speculation about the consequences of having global or regional learning. The impact of non-global learning is better appreciated for the situation where trade across all regions is allowed. Figure 57 and Figure 58 present the comparison of the generation mix for the Annex I and non-Annex I groups in 2050, for the Kyoto for ever scenario (full trade), when global and regional learning are considered.

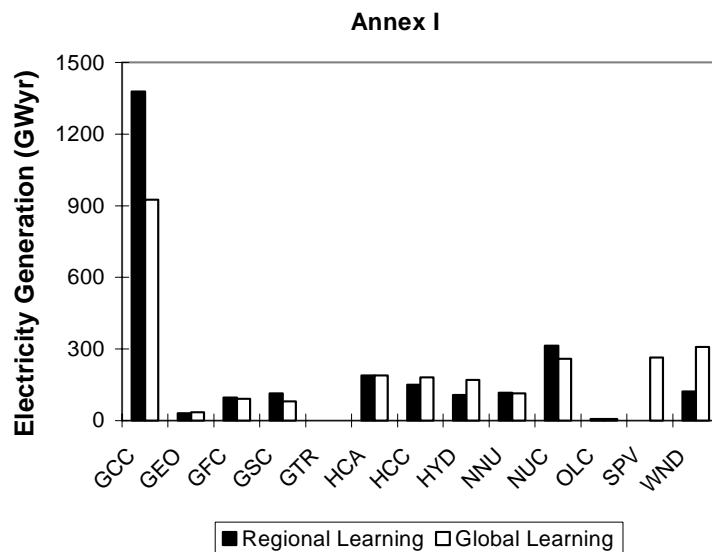


Figure 57. Electricity generation mix in 2050. Annex I group. Global Vs Regional learning.

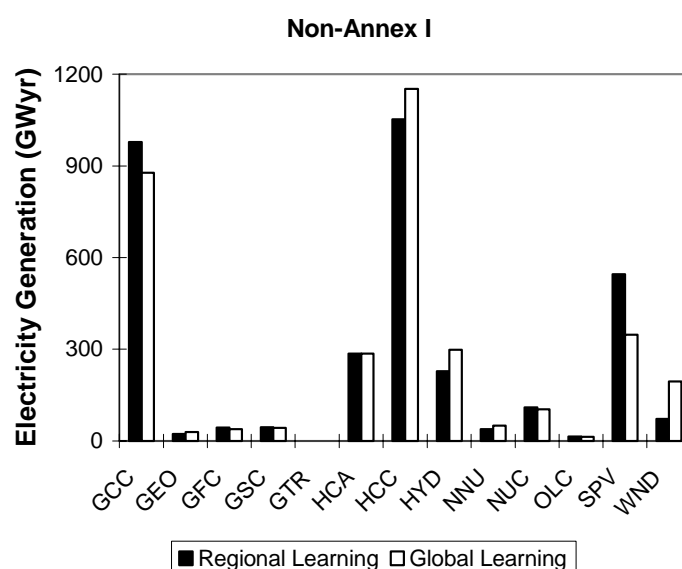


Figure 58. Electricity generation mix in 2050. non-Annex I group. Global Vs Regional learning.

As expected, restricting the size of the learning regions affects the cost competitiveness of the technologies and, consequently, their ranking and generation output. As both groups are decoupled, no spill-over across them occurs and, thus, none of them can profit from the cost reductions taking place in the other. In this particular case, the wind turbine experiences a much lower global growth. In the case of the solar PV, the aggregated output is also reduced but to a lesser extent. However, investments in this technology are carried out almost exclusively in the non-Annex I regions while in the global learning situation they were present in both groups of countries. On the other hand, gas combined cycle turbines, already very competitive, are able to increment their electricity production in the two-learning-regions case. This model result can be

interpreted as an illustration of the fact that, if not enough opportunities exist for a given technology to accumulate the experience necessary to go down its learning curve and become competitive, it may be "locked out" from the system. The spatial aspects of technological learning are examined in more detail in chapter 6 and chapter 8.

5.7 Conclusions

Some indicative analyses concerning the future structure of the global electricity generation system under a fast growth demand scenario are carried out with the ERIS model prototype. Possible consequences of the Kyoto protocol on the structure of the generation mix and the effects of international emission trading for its fulfilment have been outlined, considering the effect of endogenous technological learning.

Fossil fuels, mainly coal and natural gas, will continue to hold a significant share of the global electricity supply in the next fifty years. Natural gas combined-cycle turbines will experience a very dynamic growth, rivalling coal plants as the prevalent generation technology. Nuclear power plants remain a robust option for electricity generation if the path to decarbonisation is to be followed. However, there are also opportunities for new, emerging technologies. Advanced, more efficient, coal power plants are likely to gain share. Wind turbines constitute a readily cost-competitive alternative in several markets. Solar photo-voltaics may be brought about in a massive way in a CO₂ constrained world. Gas fuel cells could also play an important role.

The analysis of Kyoto-for-ever and Kyoto-global-trend scenarios indicates that a significant departure from carbon intensive generation options is required to fulfil the CO₂ emission targets. However, global emissions from electricity systems will continue to grow substantially. With an endogenous representation of technology dynamics, early up-front investments are made to stimulate the necessary technological progress of emerging low -or free- carbon generation options, which are then able to play an active role in the mitigation strategy. When uncertainty in emission reduction commitments is considered, the results point also in the direction of undertaking early abatement action as a preparation for future contingencies. This early action stimulates technological learning that proves beneficial in terms of both lower costs and emissions in the long run.

The possibility of trading emission permits, either between Annex I regions or extending the trade to non-Annex I regions, will allow some regions to undertake less radical changes in their electricity sectors than what would be required otherwise. Nonetheless, trade does not rule out action in the regions with commitments. However, trade may provide incentives for the penetration of emerging learning technologies in different regions, stimulating accumulation of experience with them, and thus contributing to the progress along their learning curves towards long run cost competitiveness. In particular, international cooperation for emissions abatement between Annex I and non-Annex I countries may drive to significant deployment of new technologies in developing countries, multiplying the opportunities for technological learning as penetration occurs in markets with significant potential and attractive niche markets.

In a multi-regional framework, the representation of endogenous technological learning leads to interesting patterns of response of the model. Due to the underlying increasing returns mechanism, and the allowance of full spill-over of learning, installations of a given technology in a certain region will contribute to make it competitive in another region(s) and thus stimulate its deployment there and a further increase in cost competitiveness. The scale at which learning is allowed (global, regional) will certainly affect the possible development. The spatial dimension of technological learning and the possibilities of learning "spill-over" are aspects that deserve further investigation.

The results also show that the consideration of uncertain learning rates may drive the model to follow a more prudent path of investments in learning technologies. Other uncertainties have also an impact, stimulating or delaying technological learning. Following the statement of Grübler (1998), who stresses that uncertainty is, together with learning, at the core of the endogenous mechanisms of technological change, future work should also be devoted to a more thorough exploration of the effects of uncertainty both in learning rates and other driving forces such as demands and environmental constraints.

Competition against well established generation technologies will not be easy for emerging, less carbon intensive alternatives. If they are to play a significant role in future electricity generation markets, emerging technologies will require investments, both in R&D and niche markets, to foster their development. Therefore, their successful introduction requires a strategy that promotes innovation and learning at multiple technological, social and institutional levels.

6. Multi-regional learning in the MARKAL model

In this chapter the implementation of multi-regional endogenous technological learning in the MARKAL model is presented. A mapping procedure is implemented to group learning technologies inside one region or across several regions in a flexible way, in order to allow them to learn together. The chapter is structured as follows. First, the approach is briefly described. After, an illustrative example examining the response of a multi-regional global electricity generation system is presented. In such example, first the behaviour with global learning is examined and then sensitivity to the spatial scale of learning is carried out. The multi-regional learning framework allows the examination of the spatial interactions and mechanisms that affect the technological learning processes in global energy systems. The mutual interactions between the learning and emissions trading mechanisms are highlighted. Although emphasis is given to energy modelling, some policy insights can be gained. The results highlight the importance of fostering international co-operation to stimulate the learning process of emerging energy technologies.

6.1 Introduction

Spatial interactions at different scales are important for technological change. The creation and expansion of networks play a significant role in the diffusion of innovations (Grübler, 1996)⁵¹. Allowing interchange of information about, and continuous experimentation with, technologies, networks are also an essential element for technological learning processes, which, among other factors, play a very important role in the transformation of the technological landscape. In fact, technological learning can be seen as a network phenomenon (Wright, 1997).

The role of technology in a multi-regional context is highly relevant for energy policy making. On the one hand, the dynamics of penetration of energy technologies are different across world regions, depending on a number of factors such as available resources, economic development, technological and scientific capacity, policies, market opportunities, social acceptance etc. On the other hand, international interactions and co-operation influence the pace of energy-technology innovation. Both regional differences and multi-regional interactions and their impact on the global competitiveness of energy supply and end-use technologies must be examined.

Understanding the mechanisms of global and regional energy technology learning is necessary to define international co-operation strategies to promote the diffusion of innovative, clean and more efficient energy technologies (Koch, 1999). Thus, it is important to have adequate analytical tools to explore the spatial aspects of energy technology dynamics and particularly relevant aspects are the learning patterns.

⁵¹ From a spatial point of view, innovations are seen as diffusing from innovation centres towards a periphery. The periphery starts later the adoption process, profiting from the experience of early adopters, but tend to reach lower adoption intensities (Grübler, 1996, Nakicenovic, 1997). Although such patterns are not discussed here, they are mentioned to highlight the spatial dimension of technological change processes.

Among such tools are the energy systems optimisation models used to support energy policy analysis. One of the members of the MARKAL family of models is the multi-regional RMARKAL model, which allows the examination of several coupled energy systems as a single model, taking into account global or bi-lateral trade of energy carriers and emissions (Decisionware, 1997). It is a flexible tool for studying mechanisms of international co-operation for emission reductions such as trade of emission permits, Joint Implementation and the Clean Development Mechanism⁵².

The endogenisation of learning curves is extended here to the multi-regional RMARKAL and modifications are done in order to allow technologies learning across regions, thus enabling the explicit consideration of learning spill-over between regions and incorporating a spatial dimension to the technological learning processes. The approach is described, an illustrative application presented and some insights gained out of the exercise are discussed.

6.2 Description of the approach

In order to allow capacity accumulated across different regions on similar (related) technologies to contribute to the cost reduction, dummy technologies are defined in the multi-regional model. They correspond to sets of actual regional learning technologies. Using a mapping set, the user specifies the regional technologies that compose a multi-regional aggregate one. Cumulative capacities of those technologies are added up to obtain the cumulative capacity of the aggregate learning one, which is used for the computation of the corresponding investment costs.

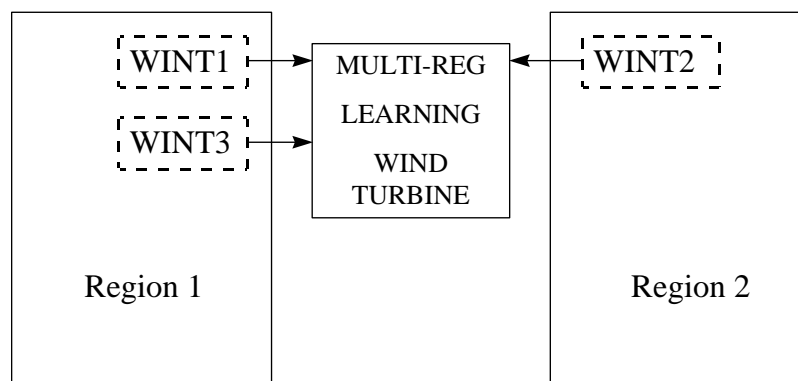


Figure 59. *Definition of multi-regional dummy learning technologies.*

The variables, parameters and equations are defined in function of the set of aggregate learning technologies, and not in terms of the actual regional learning technologies. With this formulation, several technologies belonging to the same or different regions may be associated to an aggregate one. This also facilitates the representation of inter-regional clusters of technologies.

There is no explicit reference to "learning regions" in this approach. The geographical scale of learning is implicitly defined by the mapping set. An alternative to the procedure used here is the definition of global technologies that could be installed

⁵² For applications of the Multi-Regional MARKAL model to Joint Implementation and CDM analysis see, for instance, Kanudia and Loulou (1998) or Bahn et al. (1999).

across different regions and the specification of "learning" regions for those technologies. A "learning region" being defined as the set of regions across which cumulative capacities should be added for a given technology. Then, a corresponding mapping set between actual and "learning regions" should be defined. Such approach was, in fact, followed by the author in the multi-regional version of the ERIS model, where a unique set of technologies is specified, being some of their attributes made regional. In the MARKAL model, however, definition of global technologies would have implied an unnecessary restriction.

As before, it is important to notice how this representation of learning influences the outcome in a multi-regional framework. The approach implicitly assumes that the investment costs are the same for all the regions that conform a given spatial learning domain. As cumulative capacities are added up across regions in order to compute the investment costs, installations of a given technology in one region will affect the uniquely defined investment cost and can make it economic in another region that belongs to the same spatial learning domain.

Several aspects should be taken into account when considering technological learning in the multi-regional context. One of them is related to the very application of multi-regional learning to a given technology. The assumption that the deployment of a technology in some regions of the world contributes to the learning process in other regions could be questionable in some cases. Important sources of learning could be more related to, for instance, knowledge spillover from other industries or technologies using similar production methods⁵³, rather than to installations of the same (or a similar) technology in other regions of the world.

But, on the other hand, globalisation of the energy markets with competition and knowledge interchange occurring all around the world may promote a global learning process for some technologies (Kydes, 1999)⁵⁴. Also, international co-operation efforts may stimulate spillover of learning between national R&D and deployment programmes, helping to reduce cost barriers for the introduction of emerging energy technologies (Koch, 1999). However, international learning should not be taken for granted for all the technologies. For several promising, but still expensive, energy technologies a true "global" technological learning process will require continuous and co-ordinated international efforts involving both public and private actors in order to provide the opportunities that enable them to move along the experience curve (PCAST, 1999, Wene, 2000). Also, a technology can be composed of several learning sub-

⁵³ In the case of solar photo-voltaics, for instance, the technology may have benefited from some experience and manufacturing procedures coming originally from the micro-electronics industry (Benner and Kazmerski, 1999)

⁵⁴ Accompanying the globalisation of the economy and linked to privatisation processes in the energy sectors of many countries, the world has seen the rise of international, multi-purpose and highly integrated, energy companies (EIA, 1996). These companies play an important role in international learning processes of energy technologies. However, privatisation in the energy sector also implies that the technology choices are driven by short-term profitability criteria. This certainly may render technologies with long-term returns unattractive, even if they offer benefits from a public interest perspective. Thus, although the private sector will most surely play the major role in the international energy markets, multi-lateral government intervention will help to fill the gaps in private sector investment, relying on a much longer term perspective, necessary to stimulate the learning of clean, radical emerging technologies and their penetration into the marketplace (PCAST, 1999).

systems each exhibiting a different spatial scale of learning (Wene, 2000). The scale of learning can be multi-regional for some components but local for others⁵⁵.

Concerning this issue, further research is required in order to conceive a coherent treatment of the spatial interactions that affect learning. Case studies of the spatial dynamics (or "innovation geography") of particular technologies or groups of technologies must be undertaken to facilitate the definition of the scale at which the process occurs.

6.3 An illustrative example

The new features are used to examine the behaviour of a multi-regional MARKAL model of the global electricity generation system in order to examine its technological trajectories under different scenarios. As in the analysis performed with ERIS in chapter 5, the regions have been chosen following those of the MERGE3 Model (Manne and Richels, 1997). Results are presented mainly at the aggregate global level or for Annex I and non-Annex I groups or regions.

Although the case study is similar to the one undertaken with ERIS, different aspects are emphasised. Some changes were introduced in the technical parameters of some technologies. In particular, following EIA (1998), a more optimistic assumption has been considered for the variable operation and maintenance cost (Var. O&M) of the fuel cell power plant. In addition, MARKAL provides a more sophisticated treatment of a number of modelling aspects. Specifically, seasonal availability factors are applied to renewable technologies. Also, contributions of the different plants to peak and base load are distinguished and a number of parameters (e.g. efficiency) are time-dependant. Furthermore, the CO₂ constraints applied are different here. Therefore, the results are not directly comparable.

The basic parameters for the technologies competing in the electricity generation market considered here are presented in the Table 1. Their technical characteristics are assumed equal across regions. Cost figures are in 1998 US dollars. Six technologies are considered to exhibit learning. For the segmentation with the MIP approach, a maximum cumulative capacity of 6000 GW and eight segments are used for all of them. For all the model runs a discount rate of 5% is used.

⁵⁵ Wene (2000) mentions solar photo-voltaics as an example, where PV modules exhibit an international learning process while learning in the Balance-of-Plant (BOP) depends on local conditions.

Technology	Abbrev	Inv. Cost (US\$/kW)	Fixed O&M (US\$/kW/year)	Var. O&M (US\$/kWyr)	Efficiency (Fraction)	Progress Ratio
Conventional Coal	HCC	1357	69	22.7	0.39	1
Advanced Coal	HCA	1884	67.5	23.6	0.45	0.94
Gas Steam	GSC	987	50.6	17.7	0.41	1
Gas CC	GCC	600	36.6	19.7	0.51	0.90
Gas Turbine	GTC	350	58.5	16.03	0.36	1
Gas Fuel Cell	GFC	2463	43.5	20.	0.65	0.82
Oil Steam	OLC	1575	63.6	18.13	0.38	1
Nuclear	NUC	3075	114	5.91	0.34	1
New Nuclear	NNU	3400	114	5.91	0.36	0.96
Hydro	HYD	3562	49.5	3.9	0.70	1
Solar PV	SPV	4600	9.	39.4	0.1	0.81
Wind	WND	1035	13.5	26.3	0.33	0.90
Geothermal	GEO	3075	7.8	92	0.3	1

Table 8. *Main characteristics of electricity generation technologies.*

The electricity demand corresponds to the same REFXII/A2 scenario used above. As for emission constraints, two basic CO₂ emission scenarios have been examined. The first is a "Business-as-Usual" scenario that reflects a CO₂ unconstrained development. The second is a "Kyoto-trend" scenario. Annex I regions reach their Kyoto-agreed targets⁵⁶ by 2010 and afterwards they follow a linear reduction from this target of 5% per decade until the end of the horizon. For this CO₂ constrained scenario, three variants are examined concerning trade of emission permits. In the first one, no trade is allowed. In the second one, trade is allowed only between Annex I regions starting from 2010. In the third one, non-Annex I regions join trade of permits in the year 2030. In order to avoid carbon leakage, in the constrained scenarios non-Annex I regions are bounded to their BaU baseline emissions.

6.3.1 Global learning

Results are presented first for a reference situation that assumes global learning. That is, all regions contribute to the reduction of investment costs. The influence of changing the geographical scale of technological learning on the technology choice in the model is examined below in numeral 6.3.2.

6.3.1.1 Business-as-Usual scenario

Figure 60 presents the evolution of global electricity generation in the unconstrained situation ("Business-as-Usual"). Coal continues to be an important primary source. Although mainly conventional coal-fired plants are deployed, clean coal technologies progressively gain market share in this scenario. In fact, conventional plants begin to experience an absolute decline of production after 2030. Oil power plants are phased out. The natural gas combined-cycle turbine, already one of the most competitive options in many countries of the world (Paffenbarger, 1999), experiences a highly dynamic growth. Conventional nuclear generation declines but new nuclear power plants gain share. The gas fuel cell and wind turbines also penetrate the market. Solar photo-voltaics, however, remains "locked-out" of the system.

⁵⁶ It is assumed that the targets are applied directly to the electricity system.

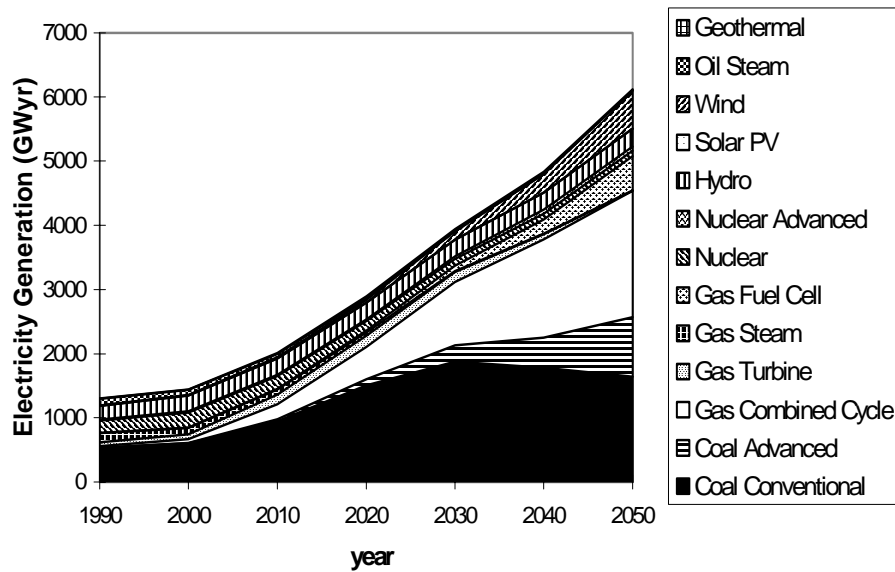


Figure 60. *Global electricity generation. BaU scenario. Global learning.*

The corresponding regionalised CO₂ emissions are shown in Figure 61. A substantial increase occurs along the horizon, with emissions from the developing regions becoming increasingly important. However, the penetration of new, more efficient and less carbon intensive generation alternatives produces a slow-down in the growth of emissions, evident after 2030.

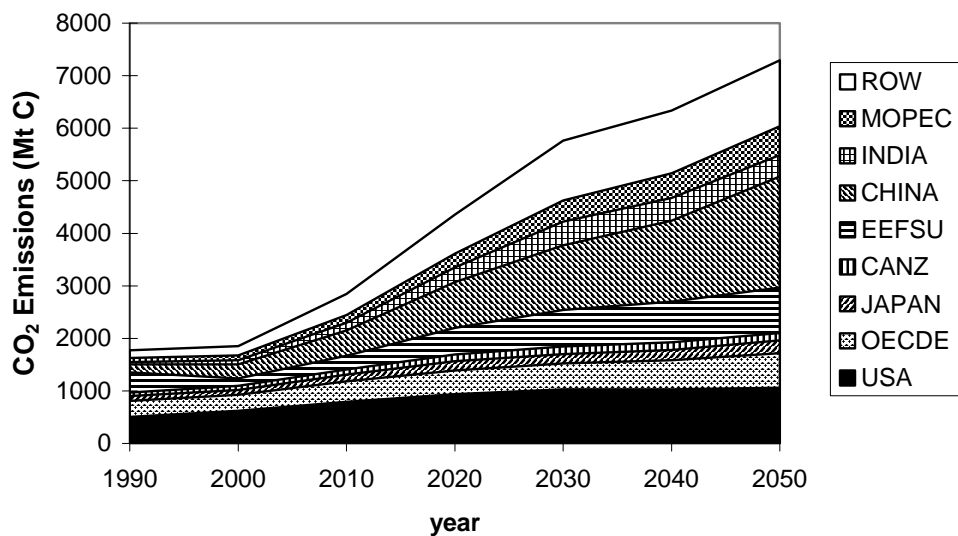


Figure 61. *CO₂ emissions from the global electricity system. BaU scenario. Global learning.*

6.3.1.2 Kyoto trend scenario

The behaviour of the system under the Kyoto trend target is now examined. Figure 62 presents the global electricity generation mix for the variant of trade of emission permits

only among Annex I regions⁵⁷. The output of coal-fired plants, both conventional and clean, is reduced in this scenario, while the production of nuclear technologies, both conventional and advanced, is substantially increased. Gas combined-cycle turbines and fuel cells reduce their global output. Wind turbines do not show a further increase, as they were already penetrating at their maximum growth rate in the BaU scenario. Solar PV penetrates to a certain extent.

The corresponding regionalised emissions are depicted in Figure 63. Emissions in developing regions are slightly reduced due to a higher, though not significantly, penetration of some less carbon intensive alternatives such as combined-cycle turbines and wind turbines, because of the global learning spillover effect. This is an interesting effect, because provides an indication of the possible positive effects of the innovation process induced by abatement action in industrialised countries, which would be a counteracting force to the classical negative "leakage" effects discussed in the literature (Grubb et al., 2000). It also illustrates how global emission profiles depend on the presence and magnitude of international technology spillover.

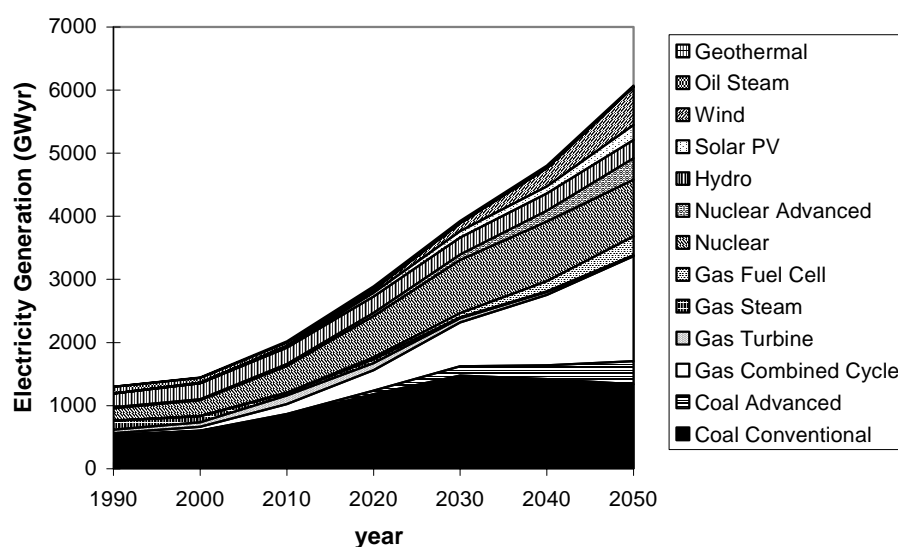


Figure 62. *Global electricity generation. Kyoto trend scenario. Trade in Annex I regions. Global learning.*

⁵⁷ In the situation without trade the evolution of the global generation mix is, with some minor differences, very similar to that of the trade in Annex I case and is not discussed or shown here. The emission trajectories of Annex I regions are, of course, different. The results for the year 2050 are presented for comparison in Figure 64 to Figure 67.

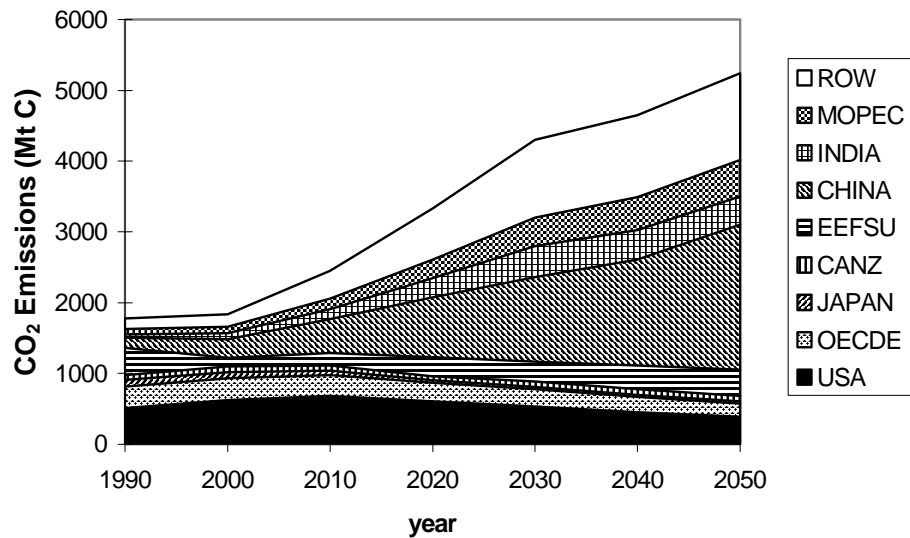


Figure 63. *CO₂ emissions from the global electricity system. Kyoto trend scenario. Trade in Annex I regions. Global learning.*

With full trade, parts of the commitments of the Annex I regions are fulfilled by buying CO₂ permits from the developing world. Annex I regions are allowed to increase carbon-intensive generation, while non-Annex I regions are stimulated to reduce it. Under those counteracting forces, the global aggregated generation mix does not change substantially respect to the previous constrained cases, although the Annex I/non-Annex I dynamics is markedly different (as seen below). Still, total coal-fired generation increases slightly respect to the previous Kyoto trend variant, with clean coal technologies playing a much more important role. Also, output of combined cycle turbines and gas fuel cells is slightly augmented, while that of conventional nuclear is reduced in comparison to the previous case. Correspondingly, global emissions are somewhat higher.

Figure 64 presents the comparison of the electricity generation mix for the year 2050 under the different CO₂ scenarios considered. Figure 65 presents the corresponding comparison of regionalised CO₂ emissions.

Electricity production continues to rely to a significant extent on fossil fuels. However, important structural changes of the fuel mix can be observed in both scenarios. Coal remains an important source to meet the fast growing electricity demand and contributes to a significant increase of associated emissions. However, more efficient clean coal technologies are able to gain a sizeable share of the coal-fired generation. The contribution of coal is, as expected, much less substantial in the Kyoto trend scenario. Natural gas, a cleaner and more flexible fossil fuel, plays an increasing role as a primary source for power supply, as gas combined cycle turbines experience a very dynamic growth along the time horizon and fuel cells penetrate the markets. Wind turbines, already cost-effective in a number of markets, play also an active role. Early adoption of emerging technologies with high learning potential such as fuel cells occurs already in the reference scenario. Solar photo-voltaics becomes active in the Kyoto-trend cases.

Nonetheless, nuclear generation, from both conventional and new plants, plays a very important role in achieving the reduction targets⁵⁸.

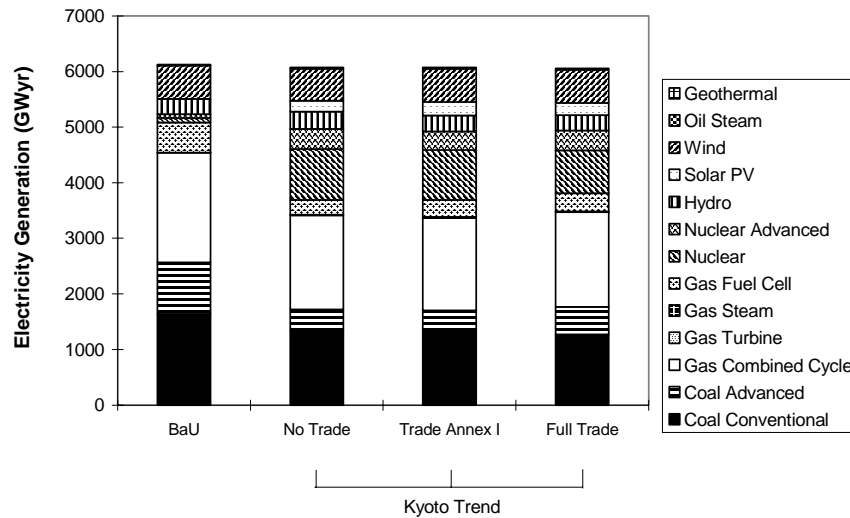


Figure 64. Comparison of global electricity generation in 2050. Business-as-Usual and Kyoto trend scenarios. Global learning.

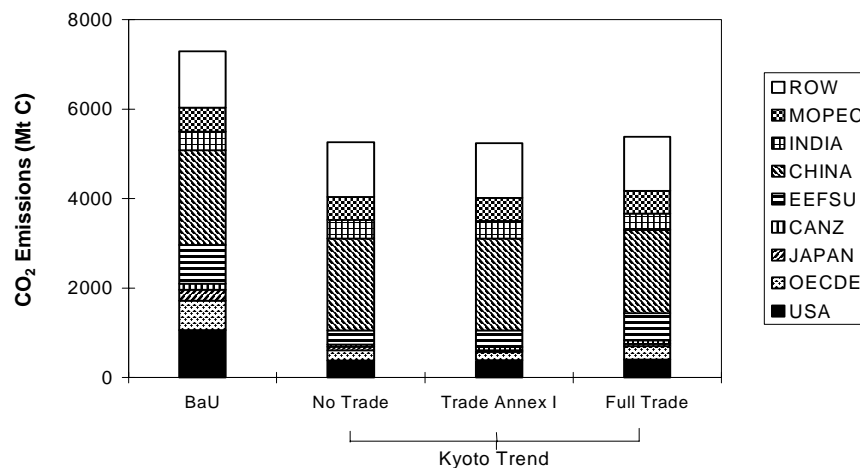


Figure 65. Comparison of regionalised CO₂ emissions in 2050. BaU and Kyoto trend scenarios. Global learning.

Figure 66 and Figure 67 present a comparison of the generation mix in the Annex I and non-Annex I groups under the BaU and the Kyoto trend scenarios. The Annex I group, being the one with emission reduction commitments, experiences more significant changes in the constrained scenarios. Without trade or with trade only among Annex I regions, coal and gas-fired electricity production are substantially reduced while nuclear output is considerably increased. The constraint also allows the introduction of solar photo-voltaics in both groups. As non-Annex I regions do not participate in the trade,

⁵⁸ In these examples, growth of nuclear electricity generation (both conventional and new plants) accounts for the bulk of emission reductions and as a significant fraction of such installations occur in the Annex I regions, this reduces the opportunities for other technologies and also diminishes the trade with the non-Annex I. Given the political and social restrictions that the development of nuclear power may face in several regions in the future, it would be interesting to examine alternative scenarios with a more restricted availability of nuclear power.

the penetration of this technology in the non-Annex I group can be seen as a consequence of the already mentioned global learning assumption. Deployment in Annex I regions reduces the cost and drives to increased competitiveness also in non-Annex I ones. Thus, as a consequence of such learning spillover, non-Annex I regions already experience some reduction of their emissions from the binding reference values.

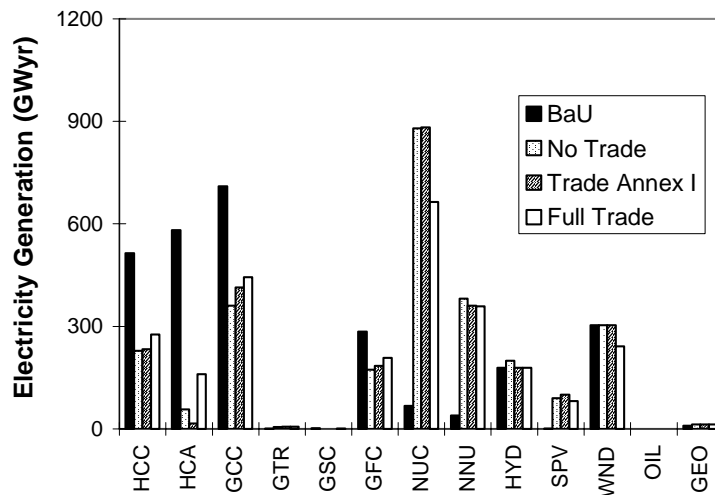


Figure 66. Electricity generation in the Annex I group in 2050. BaU and Kyoto trend scenarios.

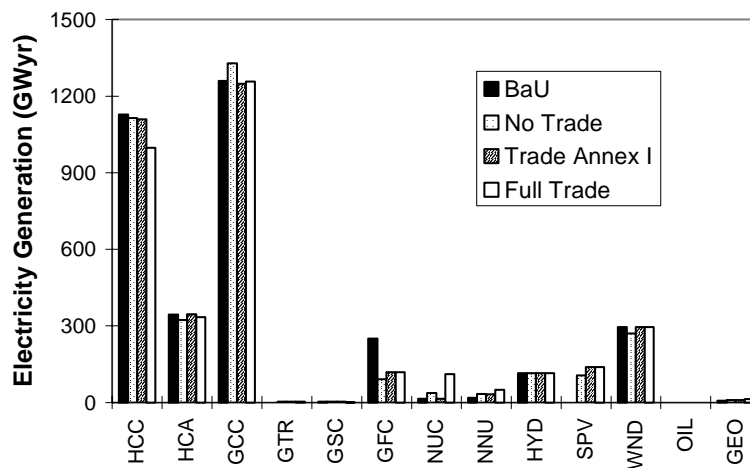


Figure 67. Electricity generation in the non-Annex I group in 2050. BaU and Kyoto trend scenarios.

The extension of trade of emissions to non-Annex I regions allows a less significant departure from carbon-intensive technologies in the Annex I group as they buy permits from the non-Annex I group. However, in this latter group, besides substitution of nuclear for coal-fired generation, structural changes are not substantially different from those already undertaken in the previous Annex I-only trade situation. But, while in the other cases learning spillover was the main incentive to deploy less carbon intensive technologies in the non-Annex I group, with the allowance of full trade the fact that

emission credits provided by the installation of low-carbon technologies can be sold to Annex I regions constitutes the main stimulus for their deployment. Of course, learning spillover still plays a role and interacts with the trade mechanism.

Finally, Figure 68 presents a comparison of the evolution of the carbon intensity of the global electricity generation system for the BaU and the Kyoto-trend scenarios.

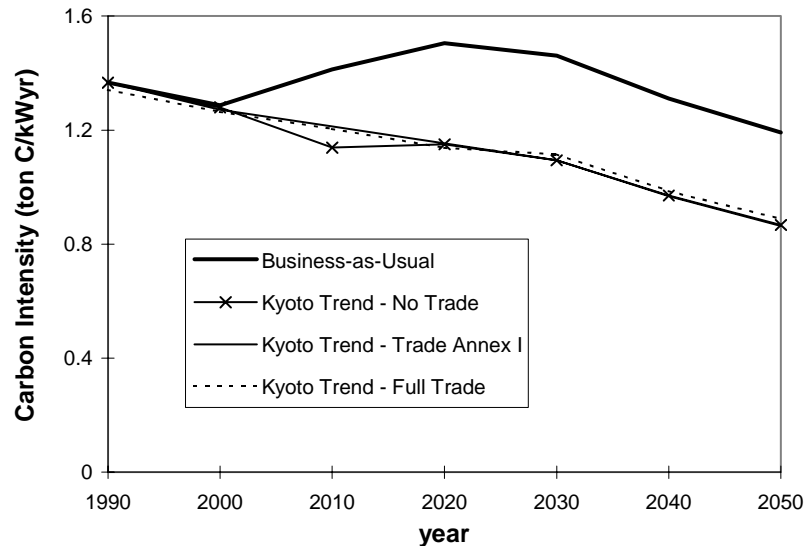


Figure 68. *Evolution of the carbon intensity of the global electricity system. Global learning.*

In the BaU scenario, a recarbonisation process takes place up to 2020, as carbon intensive technologies continue to grow appreciably to meet the fast increasing demand and low-carbon ones, although dynamically growing, are not yet significant contributors. After 2030, the system reverses this trend and a decarbonisation path is set again as new, less carbon intensive technologies gain sizable shares of the generation market. On the Kyoto-trend scenario, a progressive decarbonisation process occurs along the whole horizon, with an approximate average rate of 0.8% per annum for the 1990-2050 period.

6.3.2 Sensitivity to the spatial scale of learning

So far in this analysis the learning process has been assumed to occur at the global scale. However, for some technologies learning could take place at a different scale depending on a number of factors influencing the activities of both private and public incumbent actors across countries and regions. In order to examine the influence of the geographical scale at which technological learning takes place, two additional learning scenarios are analysed. In the first one, learning occurs at the single region level. That is, only the capacity deployed in a given region counts for the investment cost computation using the learning curve. In the second one, two "learning" regions are specified: Annex I and non-Annex I groups of countries. No spillover across "learning" regions is assumed. As a simplification, it is assumed that the same learning curves used previously in the global learning situation are valid in both of these cases. That is, both

the starting points and the progress ratios were considered the same for all the cases⁵⁹. Also, the same learning domain is applied for all the technologies.

The definition of the spatial boundary of the learning process for these two cases is arbitrary and carried out solely for sensitivity purposes. In fact, the dynamics of international learning are highly complex and the definition of the spatial learning domain of a technology, or group of technologies, may be difficult given the number of factors that intervene in shaping it, such as commercialisation strategies and scale of operation of the firms involved, existence of international co-operation programs, creation of networks of actors etc. The modeller, however, should bear in mind that the spatial scale of the learning process does matter and may affect the results. Sensitivity analyses are useful to examine the effects of co-ordinated deployment strategies between different regions.

6.3.2.1 Comparison of global electricity generation

The aggregate global results are compared to the previously presented global learning situation. Figure 69 presents the comparison of the global electricity generation in the year 2050 for the BaU scenario and the different variants of the CO₂-constrained scenario, under the three modalities of spatial learning.

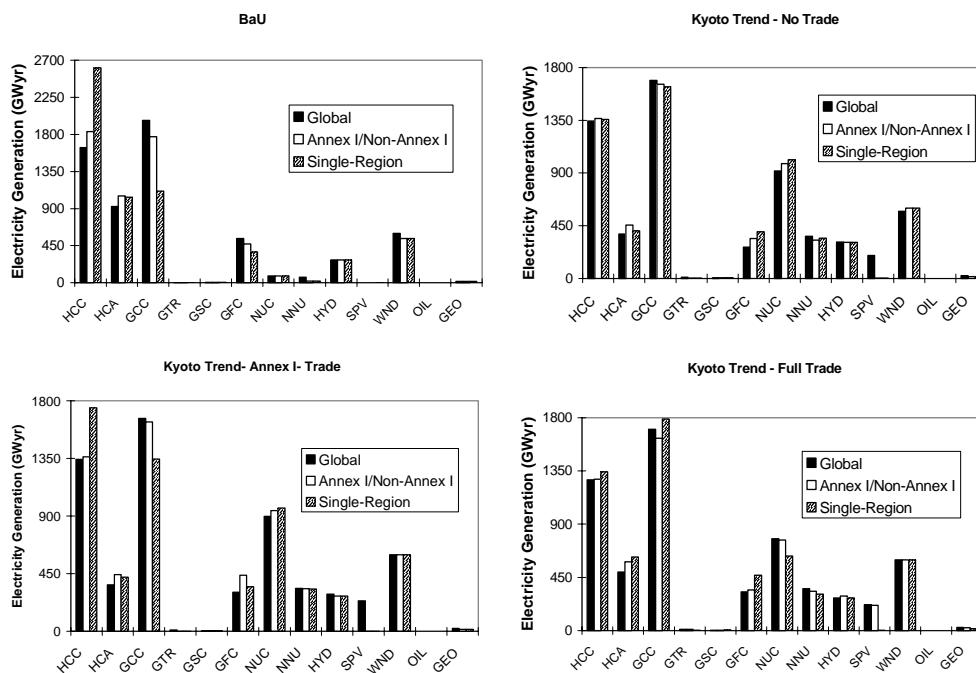


Figure 69. Global generation in 2050. Different learning scales and CO₂ constraints.

⁵⁹ Of course, in order to be consistent, ideally regional estimated learning curves should be used when learning is assumed regional and global curves when assumed global. However, lack of data in one case or the other may preclude such desirable situation.

The outcome is, as expected, altered. The ranking of the different technologies is affected by the variation of the geographical scale. The pattern of variation of the learning technologies, however, is not consistently one of reduced market share with reduced learning domain, as it depends on the competition with other technologies. Loss of market share for some of them implies higher market penetration for others.

In the BaU scenario the most significant variations occur in the relative role of two major competitors: conventional coal and combined cycle gas turbines. As the spatial scale of learning is reduced, the learning speed and consequently the cost competitiveness of the combined cycle turbine suffer. Thus, coal-fired plants increase their output in detriment of the combined cycle gas-fired generation. The role of other technologies is also affected with the reduction of the scale of learning. In particular, the gas fuel cell, the wind turbine and the new nuclear power plant lose market share while that of the clean coal technology increases.

Being learning assumed mainly for low-carbon technologies, the variation of its scale most likely affects more the expensive low-carbon or zero-carbon technologies, even if they exhibit a high learning rate. With less learning co-operation the opportunities for more expensive clean technologies to reach cost competitiveness are reduced and no emissions restriction forces them into the solution. As a consequence, the reference global emissions increase in the Annex I/non-Annex I and single-region learning cases compared to the global learning one. The single-region learning case presents the highest reference emissions (see Figure 70). As discussed below, this will also affect the trade of emission permits.

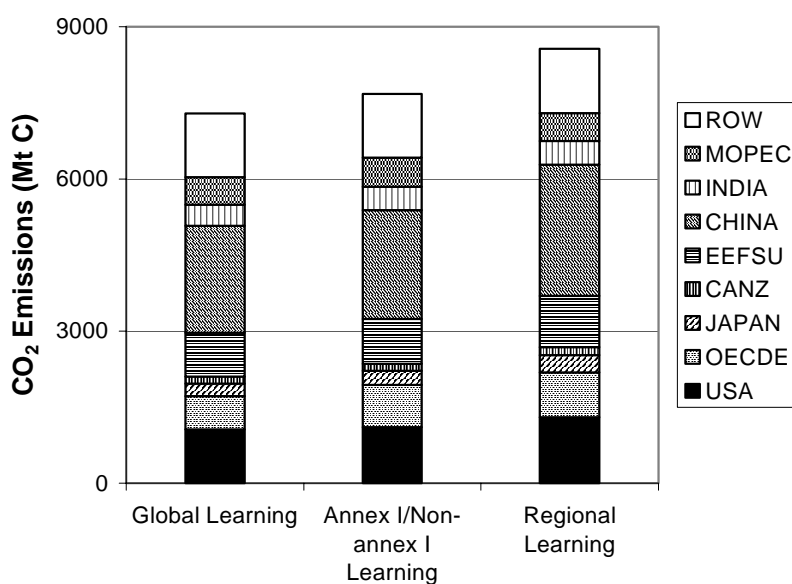


Figure 70. *Baseline CO₂ emissions in 2050. Different scales of learning.*

In the CO₂ constrained scenarios the changes in the generation mix are less considerable but still significant. It is interesting to contrast the behaviour of the wind turbine with that of solar PV. The wind turbine results competitive in all the cases. Its output is

barely altered⁶⁰. On the other hand, solar PV is a marginal technology and is substantially more affected by the variation of the spatial scale⁶¹. The gas fuel cell also experiences significant variations. In the BaU scenario, both the gas fuel cell and combined-cycle gas turbine lose terrain against coal-fired power plants. In the constrained scenarios, however, as the scale of learning shrinks, loss of market share for solar PV and the combined cycle gas turbine appears to imply a gain of share for the gas fuel cell.

6.3.2.2 Comparison of trade of CO₂ permits

It is also interesting to compare how the trade of emission permits is affected by the variation of the scale of learning. Figure 71 presents the total volume of trade for the two trade variants and the different modalities of learning.

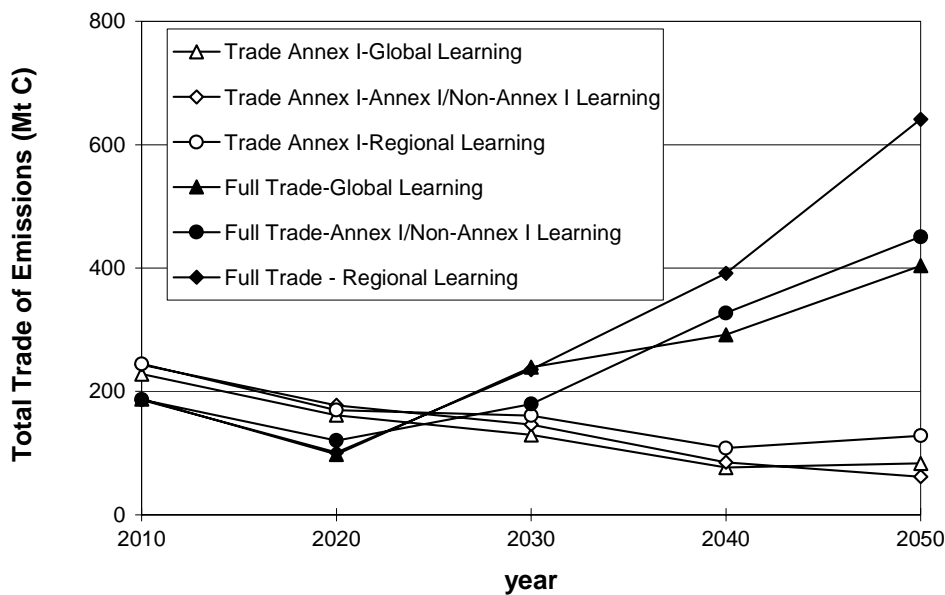


Figure 71. Comparison of the total volume of permits traded per period.

In both modalities of trade the volume of transacted permits is higher for the regional learning situation due to the higher reference emissions mentioned above. In such scenario, in several regions (e.g. CHINA and USA) isolated learning is not sufficient to bring low-carbon technologies to the market and, therefore, coal-based technologies reach a higher market share. Thus, such regions are endowed with higher baseline emissions. For buying regions this means that a higher amount of permits must be bought in order to fulfil the target. For selling regions this implies an increase in the amount of permits that can be sold without having to effect more significant structural changes in the generation mix. With the same generation mix, the regions are able to

⁶⁰ Here, one should also notice that this represents a case of "lock-in", typical in models with endogenous technological learning. Due to the underlying increasing returns mechanism, once a learning technology is chosen, it will be installed more and more, as the increasing cumulative experience makes it increasingly cheaper.

⁶¹ In previous analyses (Barreto and Kypreos, 1998b, and Seebregts et al., 1998), it was already noticed that marginal learning technologies are much more sensitive to variations of parameters such as the progress ratio or the maximum growth rate.

sell more permits in the regional learning case than in the Annex I/non-Annex I or the global learning cases.

In the Annex-I-trading case the EEFSU dominates the exports in the first periods. Although part of such exports corresponds to the "carbon bubble" created by the economic collapse of this region, the remaining exports consist of additional abatement measures undertaken under the inducement of trade. The technologies deployed and their amount varied depending on the learning scale applied but, in general, with the incentive of trade early deployment of low-carbon technologies takes place. In some cases such early deployment can be attributed to the learning mechanism being set in motion, but the fact that the perfect foresight model forces early deployment in order to meet maximum growth constraints allowing higher penetration in subsequent periods also plays a role.

With full trade after 2030 the total volume of exchanged permits increases substantially in all cases. The higher availability of low-cost abatement measures makes the regions facing constraints to rely more on imports of permits. However, permit flows in the first periods (2010-2020, before the non-Annex I regions join) are lower than those of the trade-in-Annex-I case. Volume of trade is lower due to the fact that the main selling Annex I region, EEFSU, can also buy permits from the non-Annex I countries from 2030 onwards. With perfect foresight, the offer of cheaper mitigation options available in subsequent periods diminishes the incentives for early deployment of low-carbon technologies there. As this region dominates the trade in those periods, the total volume of transacted permits decreases. However, this produces an additional effect: it allows other Annex I regions to assume a more important role as permit sellers in the remaining market. Both of these effects play a role in the deployment of learning technologies as discussed in the example presented below.

6.3.2.3 A closer look to the deployment of solar photo-voltaics

The deployment of solar PV is now examined in some more detail, as an example of a technology that increased its competitiveness as the spatial domain of learning was augmented. For the discussion the attention is concentrated on the aggregate electricity output of this technology in the Annex I and non-Annex I groups of regions. Two basic mechanisms of interaction between the two groups are present in the model, namely trade of emissions and learning spillover. Figure 72 summarizes their presence/absence in each of the cases examined here. For instance, in the case of Annex I/non-Annex I learning and full trade, only the trade mechanism provides a linkage between the two groups of regions.

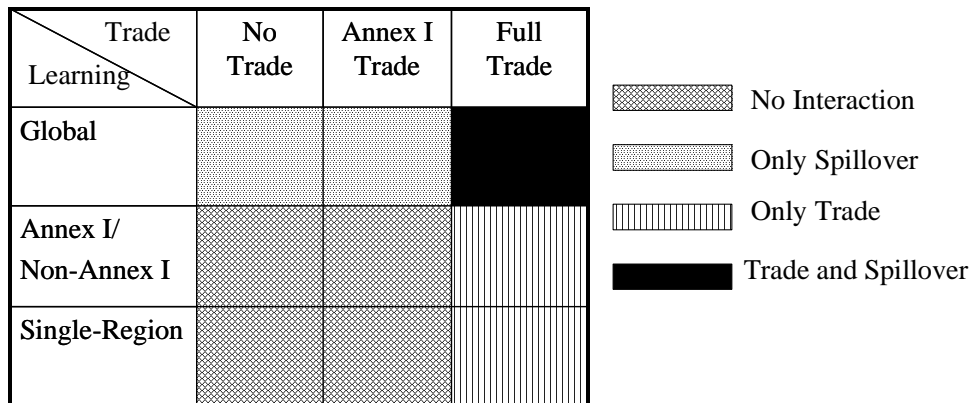


Figure 72. Interactions between Annex I and non-Annex I groups.

Figure 73 presents the electricity generation of this technology in 2050 in the Annex I and non-Annex I groups for the different CO₂ scenarios under different spatial scales of learning.

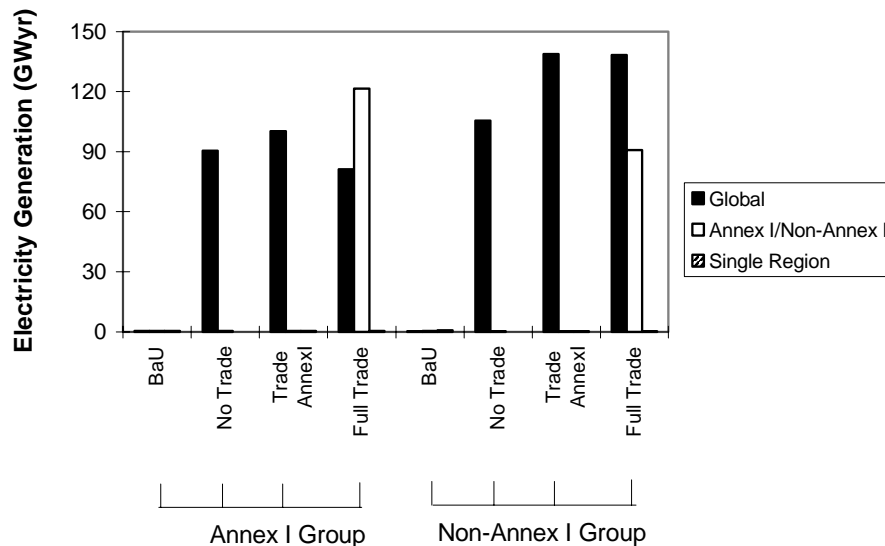


Figure 73. Electricity generation of solar PV in 2050 in Annex I and non-Annex I Groups. Comparison across CO₂ and learning scenarios.

When learning takes place at the regional scale the technology remains "locked-out". Trade is the only active multi-regional mechanism, as learning only operates inside each region. There is no spillover at all across regions. The incentives provided by trade alone are not sufficient to bring the technology into the solution. With each region depending only on its own cumulative capacity to reduce costs, the learning process is slowed down and the technology does not become attractive.

If learning is allowed in separate Annex I/non-Annex I groups the technology is introduced only in the Kyoto trend scenario with full trade. Deployment occurs in both groups, although installations are higher in the Annex I group. The interaction between Annex I and non-Annex I groups is still provided by the trade mechanism. The learning processes of Annex I and non-Annex I groups are still decoupled, so spillover across them does not occur. However, the technologies may profit from the cumulative

learning within their own coalition. Thus, cost reduction potential is higher in both groups than in the previously described single-region learning situation. Even so, solar PV continues to be unattractive in the no trade or restricted trade situations, but it becomes part of the solution in the full trade case. Clearly, the incentive provided by the trade mechanism triggers the installation of solar PV in the non-Annex I regions.

The deployment in the Annex I group is due to a more complex interaction. As mentioned before, in the full trade case trade flows in the first periods (2010-2020, before the non-Annex I regions join) are lower and the composition of sellers/buyers is altered. The smaller amount of permits sold by the EEFSU discourages the deployment of low-carbon technologies there but allows other Annex I regions to assume a more important role as permit sellers. This latter effect is instrumental in the deployment of solar PV. It counteracts and offsets the lack of incentive to deploy in the EEFSU. Even more, as the whole Annex I group acts as a single learning domain, the technology is deployed in all the regions belonging to it⁶². With these critical investments in place, the increasing returns mechanism is sufficient to keep the technology growing along the horizon, despite the offer of permits from non-Annex I countries after 2030.

When learning is allowed at the global scale the technology is introduced in all Kyoto trend cases in both groups of countries. Without trade of emissions, learning is the only active multi-regional mechanism. Learning spillover from Annex I regions stimulates penetration of the technology in non-Annex I regions. With trade among the Annex I regions, installations in both the Annex I and Non-Annex I groups are increased compared to the no trade situation. Higher deployment in Annex I trigger also a larger penetration in the non-Annex I group.

When full trade is possible, deployment in Annex I regions decreases while that in the non-Annex-I group remains at the same level of the trade-in-Annex-I situation. Two counteracting effects intervene in the deployment of the technology under this situation. On the one hand, as the Annex I regions can profit from emission reduction measures in the developing world they have a disincentive to install low- or zero-carbon technologies. Thus, spillover from installations in Annex I countries to non-Annex I ones is reduced. On the other hand, full trade stimulates deployment of low-carbon technologies in non-Annex I regions, as they can sell the corresponding permits. Thus, spillover occurs "in the other direction". Growth in the non-Annex I regions and consequent cost reductions promote growth in the Annex I regions.

In summary, the technology benefits from a larger learning domain. Or, formulated in another way, the "de-coupling" of the technological learning processes of the different regions reduces its attractiveness. The effects of trade of emission permits are also noticed. Although their individual influence may not be easy to differentiate, both mechanisms interact and play an important role in the deployment of a particular technology. The final result is a combination of these and other factors such as growth rates and potentials in each region, fuel prices, the CO₂ constraints each region may face, etc.

⁶² With learning linked across regions, when the model chooses a particular learning technology it will try to install it in all the regions that belong to a spatial learning domain because doing so it can profit fully from the learning potential available.

Of course, this is only an illustrative exercise, and the interpretation of the results is not straightforward as the competitiveness of the different technologies in the different regions is altered at the same time⁶³. Nonetheless, it is an example of the effects of multi-regional co-operation mechanisms, here represented as joint learning and/or trade of emission permits, in the deployment of new technologies. Such multi-regional interactions must be studied in more detail. Among the issues that should be tackled, lies, for instance, the question if trade of emission permits inhibits or stimulates technological change, an issue that has become relevant in the climate change debate (McDonald, 2000). A more careful examination of such question is required and models with multi-regional learning could provide helpful insights.

One could think of the learning process and the trade of emissions as spatial networks whose configurations influence each other. The "topology" of both of those networks plays a role in the final outcome. It is interesting to examine how such "topologies" and the assumptions concerning their evolution on time affect the results.

The spatial configuration of trade may change depending on the regions with abatement commitments or willing to participate in the trade at a certain point in time. As for learning, its spatial domain may change along the life cycle of a given technology. A well-established technology will most likely have its "learning topology" more or less well configured (although it could also expand/shrink along the time horizon), but that of an emerging one will unfold in the future depending on a number of factors.

This should be taken into account in the analyses and sensitivity studies, not only to the spatial scale but also to the way such scale changes on time, should be undertaken. In our exercise, the scale of learning of a given technology has been assumed not to change on time. That is, if the technology is assumed to have global learning, it will learn globally along the whole time horizon. However, it could be interesting to analyse, for instance, a growing (or shrinking) learning domain, where the technology begins to be deployed in some regions and afterwards increases its learning domain as other regions begin to deploy. This could also be a way to simulate the process of spatial-temporal diffusion of the technology.

6.4 Conclusions

Endogenous technological learning is extended to the multi-regional "bottom-up" energy optimisation RMARKAL model. A mapping procedure, which enables the aggregation of regional technologies into a multi-regional learning meta-technology, is implemented. The approach is flexible, allows the consideration of learning spillover and clustering effects and is a useful tool to explore the spatial dimension of technological learning processes. As an illustrative example the evolution of a simplified multi-regional model of the global electricity generation system under Kyoto-like CO₂ constraints is presented. Three different variants of trade of emission permits and different geographical scales of the learning process are considered. Results remain,

⁶³ In this exercise the consideration of a more extensive spatial learning domain (e.g. global learning) does not automatically imply a higher penetration for a given technology, because other technologies also alter their learning domain and it will be the final relative ranking, where other aspects (such as growth rates, learning rates, initial costs, potentials, CO₂ constraints, etc.) also intervene, what matters.

of course, highly dependant on the assumptions, particularly on progress ratios and growth rates for the different technologies, but some interesting insights are derived.

The exercise illustrates the influence of spatial aspects in the learning process of energy technologies and, subsequently, in the technological trajectory of the energy system. The geographical scale of learning affects the competitiveness and ranking of the different technological alternatives in the different regions and, consequently, has an influence on the corresponding CO₂ emission profiles. The attractiveness of a given technology depends, among other factors, on its opportunities to accumulate experience relative to others. A broader spatial domain (e.g. through access to a wider range of markets) may contribute to tap its learning potential. Other mechanisms such as trade of emission permits, also having a spatial aspect, influence the outcome as well. The learning and trade mechanisms interact and exert mutual influence on each other, playing a significant role in the resulting technology mix.

The combined effects of different modalities of trade of emissions permits and different scales of learning on the technology choices in the global energy system and the associated environmental impacts must be examined further. Such analyses could, for instance, help to shed some light into questions arising in the climate change debate, concerning the possible effects of emissions trading and other geographic-flexibility mechanisms for GHG mitigation on energy innovation (McDonald, 2000).

The modelling exercise also provides some valuable policy insights. In particular, it highlights the opportunities that international partnerships may create for the diffusion of emerging technologies. Co-operation among industrialised countries and between these and developing countries in research, development, demonstration and deployment (RD³) of more efficient and cleaner energy technologies may foster international learning processes that will contribute to boost their competitiveness in the global energy markets, thus accelerating their penetration and offering long-term environmental and economic benefits (PCAST, 1999). Stimulation of international learning, however, must be balanced against, and made compatible to local requirements for a diversified technological choice according to specific needs and available natural, technological, economic and human resources (Wene, 2000). Also, as part of the efforts, and in particular to what concerns developing countries, sound technology transfer strategies with emphasis in building local capabilities must be outlined (Martinot et al., 1997).

In a world with globalised energy markets and global environmental concerns, technological learning partnerships arise as an important policy intervention mechanism whose effects on the evolution of the energy systems should be investigated. The inclusion of multi-regional learning in the models enables pursuing such endeavours. Given the dependence that global GHG emissions have on the degree of technology spillover, a topic of particular interest is the examination of emission trends and the costs of GHG mitigation in the global energy system with and without strategies of co-operative learning.

6.5 Further work

A number of challenging questions regarding the critical role of technology in the evolution of the global energy systems must still be addressed. Modelling tools should be able to contribute to a better understanding of those issues. In this regard, the modelling approach reported here and similar ones open some new possibilities. A number of topics can and should be explored.

One of them is the consideration of clusters in a multi-regional context. Having the possibility of linking several related learning technologies is important to represent mutual influences and cross-enhancements. Technological clusters may be shaped where a number of technologies interact and reinforce each other, contributing to their mutual development (Nakicenovic, 1997, Grübler, 1998). It is important to study the evolution of these interrelated clusters and how they affect the process of technological change and the penetration of emerging technologies in the energy sector.

Seebregts et al. (2000a) applied the concept of "key technology" to the European MARKAL database to represent clusters⁶⁴. A key technology is defined as one that is a component in many other technologies. In their analysis, a learning curve is specified for each key technology. The technologies specified in the Reference Energy System as possessing a common key technology are grouped in a cluster and the sum of investments on the key technology across the cluster is used to update its investment cost⁶⁵.

The mapping procedure applied here facilitates the representation of technology clusters in a multi-regional framework and can also be combined with the key technology concept. As the key technology investments are commensurate with the investments of the corresponding technologies in a (in this case regional) cluster, similar key technologies of different regions can be associated in a multi-regional aggregate one. Also, the combined use of flexible multi-regional learning and the key technology concept allows handling technologies made up of several components exhibiting different spatial scales of learning mentioned above. In such case, a technology can be specified as an ensemble of several learning sub-systems. Some of them may be part of a multi-regional learning cluster, while others may be given as regional learning

⁶⁴ It must be mentioned here that the meaning given to the concept of clusters of technologies by several authors as Nakicenovic (1997) and Grübler (1996, 1998) is more ample than that used by Seebregts et al. (2000a), because the latter only consider the particular case where the technologies directly share a common component, while the former considers a much wider range of technical, social and economic linkages. However, as mentioned by Grübler et al. (1999), the definition of the Reference Energy System in technology oriented "bottom-up" models, representing the whole chain from primary energy sources to end devices, already accounts for a number of synergies and interactions among energy technologies that contribute to the conformation of the (broadly defined) technology clusters (That is, to the extent that a formal representation of such linkages can be done in this kind of models). Here, the word cluster is used in the more restrictive sense of Seebregts et al. (2000a).

⁶⁵ Interactions between technologies not directly sharing a key technology may still impact their respective learning processes. However, from a formal implementation point of view, when cumulative capacity is being used as the variable to approximate the accumulated experience, the problem may arise as how to combine (probably) different ways of measuring such capacity.

technologies or non-learning parts. Additionally, spillover across different clusters can be considered ⁶⁶.

Also, differentiating the costs of similar technologies across regions (or in general, specifying different costs for different members in a cluster) could be desirable, if the necessary information is available. With the current approach, where a single learning curve is specified for a given multi-regional aggregate technology, or cluster, equal costs across the regions associated to a given learning region (or across technologies that belong to the same cluster ⁶⁷) are unavoidable. Thus, the following modification could be useful for such purpose. For each individual learning technology in a region a learning curve can be specified⁶⁸, but the cumulative capacity used to update the investment costs with such curve will be computed as the (weighted) addition of cumulative capacities across all the technologies belonging to the multi-regional aggregate (or cluster). Thus, although learning together, costs for each one could be derived from its own specification.

In addition, being technological learning an inherently uncertain process, more work should be devoted to the stochastic treatment of learning parameters in multi-regional energy systems models such as MARKAL. Also, another interesting topic could be the incorporation of spatial patterns of technology diffusion (Grübler, 1996), even if only in a stylised way, in the analysis framework. Doing so, their effect in the penetration of energy technologies in different regions of the world can be examined in combination with multi-regional technological learning.

A critical aspect concerns a systematic collection of empirical evidence to back the analyses. Underlying supporting data must be gathered and analysed in order to allow the sensible application of those modelling features. A careful examination of the spatial interactions affecting the learning process of specific technologies and/or clusters of technologies is necessary. Case studies of the spatial dynamics (or "innovation geography") of technologies are required in order to support the development of criteria for the selection of the spatial domain in which the learning process currently occurs or may take place in the future.

Learning regions could be assumed flexible, such that spillover between them is considered, where part of the cumulative capacity of a particular technology installed in one learning region contributes also to the cost reduction in other learning region. Petersik (1997), for instance, discusses the existence of evidence of international learning and reports that, on the basis of such evidence, an international learning component has been introduced in the learning function applied in the U.S. national

⁶⁶ Model experiments considering learning spillover across clusters of energy technologies in an stochastic energy optimisation model have been reported by Gritsevskiy and Nakicenovic (2000).

⁶⁷ Although above a multi-regional aggregate technology and a cluster of similar technologies were treated as separate entities, the concept of cluster can be extended as to encompass also the multi-regional aggregates. In such perspective, clusters can be spatial, i.e. composed by the regional variants of a given technology, or defined according to technological "proximity", namely composed by similar or related technologies within a given region, or a combination of both options. The clusters applied in this exercise have been of the multi-regional type, where for simplification it has been assumed that the same basic technology is available everywhere.

⁶⁸ But, of course, this will increase the computational burden to solve the model.

NEMS⁶⁹ model. The computation of the capital cost reduction for new electricity generation technologies in the U.S. is done including the capacity installed and operated in other regions of the world by firms competing in the U.S.

Another possibility that could be explored is the specification of weighting factors for the cumulative capacity of different regions. A lower weight may be given to those regions that, for some reason, can be considered to contribute less to the learning of a given technology. However, this will require adequate estimates or assumptions concerning the magnitude of those weights, which would reflect the significance of the spillover effects involved. The study of the structure and magnitude of international learning spillovers, however, is still in its infancy, both from the conceptual and empirical points of view. Efforts should be devoted in the future to elucidate the set of questions remaining.

⁶⁹ NEMS is the National Energy Modeling System, a set of models developed and used for energy policy analyses by the U.S. Department of Energy (Kydes, 1999).

7. Some tests with the two-factor learning curve in the ERIS model

In this chapter the ERIS model is modified in order to incorporate the effects of R&D investments, a very important contributing factor to the technological progress of a given technology, into the learning curve. For such purpose a modified version of the standard curve is applied, where the specific investment cost depends both on cumulative capacity and cumulative R&D expenditures. Different formulations have been examined. An exogenous specification of the R&D expenditures per technology can be provided or the model can choose them endogenously. Also, an alternative variable, the so-called knowledge stock, can be specified in place of cumulative R&D expenditures, in order to take into account depreciation and time lags in the knowledge accumulated through R&D. The description of those different alternatives and some preliminary illustrative results are presented. Given the amount of remaining open points concerning the formulation itself and the underlying data, the insights gained here are mainly methodological.

7.1. Introduction

The standard learning curve, as incorporated in ERIS, considers the specific investment cost of a given technology as a function of the cumulative capacity, reflecting the fact that some technologies experience declining costs as a result of their increasing adoption (Grübler, 1998). The cumulative capacity is used as an approximation for the knowledge accumulated during the manufacturing (learning-by-doing) and use (learning-by-using) of such technology. Such formulation takes into account the effects of experience due to actual deployment of technologies but does not provide a mechanism to reflect the effects of public and private research and development (R&D) efforts, which constitute an essential basis for cost reductions and performance improvements, particularly in the early stage of development of a technology.

R&D is one of the basic driving forces of technological progress, contributing to productivity increases and economic growth. It has been recognised that, although difficult to measure, the payoffs produced by R&D expenditures are high, both at the public and private levels (Griliches, 1995). In the case of energy systems, R&D investments are a fundamental factor for the development of new, more efficient and clean supply and end-use technologies. R&D is also one of the variables that government policies may affect, as private companies are likely to not invest enough in R&D from a public interest perspective. Therefore, it is important to study the main mechanisms by which R&D investments contribute to cost/performance improvements of individual technologies and to productivity increases of the energy system as a whole. By the same token, it is also interesting to gain insights about the optimal allocation of scarce R&D resources, taking into account that such allocation is influenced by expectations of market opportunities. Thus, it becomes necessary to incorporate those mechanisms into the energy policy decision-support frameworks, e.g. in energy optimisation models.

R&D and market experience can be thought of as two learning mechanisms which act as complementary channels for knowledge accumulation (Goulder and Mathai, 2000). Different approaches to include the R&D factor in the learning curve have been

reported in the literature. Grübler and Gritsevskiy (1997) present a stochastic optimisation micro model, which incorporates uncertain returns on learning due both to R&D and market investments. For that purpose a modified learning curve is used. Such curve considers cumulative expenditures instead of cumulative capacity as the proxy for accumulation of knowledge. Expenditures in both R&D and commercial capacity deployment are added up to contribute to the cumulative expenditures. Such approach, however, does not allow differentiating both contributing factors.

Kouvaritakis et al. (2000a,b) followed a different approach in POLES, a system dynamic, behavioural oriented model, where technological learning is driven by adaptive expectations (without perfect foresight). They used a modified two-factor learning curve. Such curve considers the specific cost as a function of cumulative capacity and cumulative R&D expenditures, assuming that R&D expenditures provide immediate effects. The corresponding so-called learning-by-doing and learning-by-searching elasticities are statistically estimated. Here, as a first attempt to introduce the R&D factor, the implementation of such two-factor learning curve in ERIS, a perfect foresight model, is presented.

7.2 The original formulation

For the sake of comprehensiveness of the two-factor formulation presented below, in this section the single factor learning curve formulation is presented again very briefly using the ERIS notation. In the original formulation of the experience curve the specific investment cost ($SC_{te,t}$) of a given technology te is defined as a power function of the cumulative capacity:

$$SC_{te,t}(C) = a * C_{te,t}^{-b} \quad (24)$$

With:

- $C_{te,t}$: Cumulative capacity
- b : Learning index
- a : Specific cost at unit cumulative capacity

The coefficient a can be computed with the initial point ($SC_{te,0}$, $dcap_{te}$) of the learning curve as:

$$a = SC_{te,0} / (dcap_{te})^{-b} = i_{te,rg} * (dcap_{te})^b \quad (25)$$

With:

- $SC_{te,0}$ Starting Specific Investment cost (\$/kW)
- $dcap_{te}$ Initial cumulative capacity (GW)
- $i_{te,rg}$ Specific investment cost of the technology te (\$/kW). $i_{te,rg}$ can be made region-dependent, but it is equal across regions for global learning.

In ERIS the global cumulative capacity per technology and period of time is expressed as the product of the global growth relative to the initial cumulative capacity and the initial cumulative capacity:

$$C_{te,t} = G_{te,t} * dcap_{te} = dcap_{te} + \sum_{rg} \sum_{\tau=1}^t I_{te,\tau,rg} * \Delta_{\tau} \quad (26)$$

Where:

$I_{te,t,rg}$ Annual investments on technology te in period $t-1$ in the region rg (GW)

$G_{te,t}$ Global growth factor - relative to $dcap_{te}$ - for a given technology te up to period t

Δ_{τ} : Length of the period

The expression for the specific cost given above is not applied directly in the model. The cumulative cost curve is used instead. The cumulative cost ($TC_{te,t}$) as a function of the cumulative capacity ($C_{te,t}$) is the integral of the specific cost curve with respect to $C_{te,t}$:

$$TC_{te,t} = \int_0^C SC(C) * dC = \frac{a}{1-b} C_{te}^{1-b} = \frac{i_{te,rg}}{1-b_{te}} (G_{te,t})^{1-b_{te}} * dcap_{te} \quad (27)$$

The investment costs per period for a given technology ($ICOST_{te,t}$) are computed as the subtraction of two consecutive values of $TC_{te,t}$:

$$ICOST_{te,t} = TC_{te,t} - TC_{te,t-1} = \frac{i_{te,rg}}{1-b_{te}} * dcap_{te} * \left[(G_{te,t})^{1-b_{te}} - (G_{te,t-1})^{1-b_{te}} \right] \quad (28)$$

The non-linear programming (NLP) formulation of the ERIS model uses the right-hand side of the above expression directly embedded in the objective function. Neither $ICOST_{te,t}$ nor $TC_{te,t}$ are defined explicitly as variables.

The Mixed Integer Programming (MIP) formulation applies a piece-wise interpolation of the cumulative cost curve where integer variables are required to control the sequence of segments along the curve. In the MIP formulation $ICOST_{te,t}$ and $TC_{te,t}$ are explicit variables.

7.3 The two-factor learning curve

The two-factor learning curve for the specific investment cost of a given technology is specified as:

$$SC_{te,t}(C, CRD) = a * C_{te,t}^{-b} * CRD_{te,t}^{-c} \quad (29)$$

Where:

$C_{te,t}$: Cumulative capacity

$CRD_{te,t}$: Cumulative R&D expenditures

b : Learning by doing (lbd) index

c : Learning by searching (lbs) index

a : Specific cost at unit cumulative capacity and unit cumulative R&D expenditures

As above, this expression is not applied directly in the model but the cumulative cost curve is used instead. Thus, the changes are applied to this latter one. The cumulative cost ($TC_{te,t}$) as a function of the cumulative capacity ($C_{te,t}$) can be expressed as the integral of the specific cost curve with respect to $C_{te,t}$.

$$TC_{te,t} = \int^c SC(C, CRD) * dC = \frac{a}{1-b} C_{te,t}^{1-b_{te}} * CRD_{te,t}^{-c_{te}} \quad (30)$$

Using the initial point of the standard learning curve (SC_0 , $dcap_{te,t}$) plus the initial cumulative R&D expenditures per technology ($dcrd_{te}$), the coefficient a can be now expressed as:

$$a = SC_{0,te} / \left[(dcap_{te})^{-b} * (dcrd_{te})^{-c} \right] = i_{te,rg} * (dcap_{te})^b * (dcrd_{te})^c \quad (31)$$

Then:

$$TC_{te,t} = \int^c SC(C, CRD) * dC = \frac{i_{te,rg} * dcap_{te} * (dcrd_{te})^c}{1-b_{te}} * (G_{te,t})^{1-b_{te}} * (CRD_{te,t})^{-c_{te}} \quad (32)$$

Thus, the undiscounted investment cost ($ICOST_{te,t}$), computed as the difference between two consecutive cumulative cost values, becomes:

$$ICOST_{te,t} = TC_{te,t} - TC_{te,t-1} = \frac{i_{te,rg} * dcap_{te} * (dcrd_{te})^c}{1-b_{te}} \left[(G_{te,t})^{1-b_{te}} * (CRD_{te,t})^{-c_{te}} - (G_{te,t-1})^{1-b_{te}} * (CRD_{te,t-1})^{-c_{te}} \right] \quad (33)$$

Due to the form of the term $(CRD_{te,t})^{-c}$, which now multiplies the cumulative cost (equation 32), this formulation does not intrinsically ensure that $TC_{te,t}$ values remain non-decreasing. Therefore, in principle the values of $ICOST_{te,t}$ could become negative if the R&D component produces a too steep decrease of the specific cost. Thus, additional checking is required to ensure that consistent values are obtained.

The cumulative R&D expenditures per technology ($CRD_{te,t}$) can be given exogenously or can be determined endogenously by the model. Here, both cases are examined. The corresponding description and results are presented below.

7.3.1 Exogenous R&D

In this case R&D expenditures per technology and year are exogenously specified ($ARD_{te,t}$). Adding them up on time, cumulative R&D expenditures per technology and time period ($CRD_{te,t}$) are obtained (in this case a time-dependent parameter) as:

$$CRD_{te,t} = dcrd_{te} + \sum_{\tau=1}^t ARD_{te,\tau} * \Delta_{\tau} \quad (34)$$

Where:

$dcrd_{te}$: Initial cumulative R&D expenditures per technology

Δ_{τ} : length of the period

$CRD_{te,t}$ is then used to compute the correcting factor applied to the cumulative cost, as shown above.

7.3.2 Endogenous R&D

In this case, an (here assumed global) annual R&D budget is specified (GRD_t), which is shared among the different learning technologies. $ARD_{te,t}$, the annual R&D expenditures per technology and time period, and $CRD_{te,t}$, the cumulative R&D expenses per technology and time period, are declared as variables. The global budget is distributed as follows:

$$GRD_t = \sum_{te \in TEG} ARD_{te,t} \quad (35)$$

TEG: Set of learning technologies

The formulation of the constraint as an equality assumes that all the money is expended. If the model is to be left free to choose whether to invest or not the constraint is formulated as an inequality (\geq). Below both cases are examined.

For a multi-regional model GRD_t could be expressed as the summation of regional budgets⁷⁰:

$$GRD_t = \sum_{rg} GRD_{rg,t} \quad (36)$$

Thus, cumulative R&D expenditures per technology and period of time are computed with the above stated expression, which now becomes a constraint of the model:

$$CRD_{te,t} = dcrd_{te} + \sum_{\tau=1}^t ARD_{te,\tau} * \Delta_{\tau} \quad (37)$$

$CRD_{te,t}$ is used to compute the correction factor applied in the cumulative cost computation.

The objective function is modified in order to include the R&D investments. The new objective function becomes:

$$z_{new} = z_{old} + \sum_{t=1}^T \sum_{te \in TEG} ARD_{te,t} * (1+d)^{-\Delta_t * t} * \Delta_t \quad (38)$$

With:

d: Discount rate

In addition, if required, maximum and minimum growth constraints can be specified for the $ARD_{te,t}$ as follows:

$$ARD_{te,t} \leq ARD_{te,t-1} * (1 + grrd)^{\Delta_t} \quad (39)$$

$$ARD_{te,t} \geq ARD_{te,t-1} * (1 - derd)^{\Delta_t} \quad (40)$$

Where:

grrd: Maximum annual growth rate for R&D expenditures

derd: Maximum annual decline rate for R&D expenditures

Notice that with this formulation, if both elasticities were equal, in principle the model would prefer to invest in capacity deployment rather than in R&D, because the benefits of investing in capacity are both a cost reduction and the capacity available to produce

⁷⁰ The summation would be made across the regions belonging to a given spatial learning domain, all of them if global learning is assumed.

energy, while those of R&D investments are restricted to the cost reduction only (Criqui et al., 2000).

This second formulation with endogenous R&D expenditures was applied only to the NLP version of the model, as its direct inclusion in the MIP one would produce a NLMIP problem.

7.4 Some results

In this section some preliminary results applying the modified formulation described above are presented. As a test case the simplified multi-regional ERIS model of global electricity generation applied in Barreto and Kypreos (2000a) is considered here. Results are presented at the global aggregate level. A 5% discount rate is used in all calculations.

Six technologies are considered to exhibit learning effects. The corresponding learning-by-doing (lbd) and learning-by-searching (lbs) progress ratios are presented in Table 9. Those coefficients have been taken from the statistical estimation performed by Kouvaritakis et al. (2000a,b) using cumulative capacity and cumulative R&D expenditures as explicative variables in the regression. A maximum cumulative capacity of 6000 GW was considered for all the learning technologies. Six segments were used for the piece-wise approximation and no "floor" cost was specified for any of them in the MIP version in order to keep the comparability with the NLP one, where no "floor" cost is applied.

As for the R&D expenditures, the figures applied are based on the estimates available from IEPE (2000), a database under development for the EC-SAPIENT project⁷¹. The numbers correspond mainly to the aggregation of expenditures in OECD countries, where the bulk of research activities take place. Those figures, however, cannot be considered definitive and they are used here only with illustrative purposes. There exist significant difficulties in gathering R&D related information. This is particularly so for business R&D because private manufacturers may not be willing to make their figures publicly available. Thus, the results presented here only intend to illustrate the response of the model with the new relationship.

⁷¹ Systems Analysis for Progress and Innovation in Energy Technologies (SAPIENT, 1999), a project of the Non-nuclear Energy Programme JOULE-III of the European Commission.

Technology	Abbrev.	Inv. Cost (US\$/kW)	Fixed O&M (US\$/kW/year)	Var. O&M (US\$/kWyr)	PR lbd	PR lbs
Conventional Coal	HCC	1357	69	22.7	1	1
Advanced Coal	HCA	1584	67.5	23.6	0.89	0.95
Gas Steam	GSC	987	50.6	17.7	1	1
Gas CC	GCC	600	36.6	19.7	0.76	0.98
Gas Turbine	GTC	350	58.5	16.03	1	1
Gas Fuel Cell	GFC	2463	43.5	80.	0.81	0.89
Oil Steam	OLC	1575	63.6	18.13	1	1
Nuclear	NUC	3075	114	5.91	1	1
New Nuclear	NNU	3400	114	5.91	0.96	0.98
Hydro	HYD	3562	49.5	3.9	1	1
Solar PV	SPV	5000	9.	39.4	0.75	0.90
Wind	WND	1035	13.5	26.3	0.84	0.93
Geothermal	GEO	3075	7.8	92	1	1

Table 9. *Main characteristics of electricity generation technologies.*

The initial cumulative R&D ($dcrd_{te}$) for each technology corresponds to the summation of the estimates of cumulative governmental and business R&D in 1997, the last year available in the database (see Table 10, figures are in US\$ millions of 1998). In addition, in order to set an initial condition, it is assumed that the annual R&D expenditures ($ARD_{te,t}$) for the first period modelled are also those of 1997. As for the evolution of available R&D funds along the time horizon, the illustrative scenario defined here assumes that, for this set of technologies, they are going to increase in the future. For the exogenous R&D case, the expenditures per learning technology grow at 1.5% per year along the time horizon. For the case with endogenous R&D expenditures, the R&D budget is assumed to increase at 1.5% per year along the time horizon, from a starting value computed as the summation of the expenditures in the six learning technologies for the first period. In addition, a maximum growth rate of 10 % per annum and a maximum decline rate of 15% per annum have been specified for all the $ARD_{te,t}$ variables.

Technology	Gov. R&D	Business R&D	Total R&D	Cum. Gov. R&D	Cum. Business R&D	Total Cum. R&D
NNU	749	24	773	22927	2244	25171
HCA	116	104	220	5411	3983	9394
GCC	69	1062	1131	1755	25771	27526
WND	143	266	409	2489	4361	6850
GFC	86	294	380	1406	6669	8075
SPV	211	198	409	3803	11091	14894
Total	1374	1948	3322			

Table 10. *Annual and cumulative R&D expenditures for 1997 used as the base for the model assumptions. Figures in US\$ millions of 1998.*

In order to compare the results the global electricity generation mix in 2050 under a Kyoto-for-ever constraint with full CO₂ emissions trading after 2030 is examined. For reference purposes the solutions obtained with the single-factor learning curve using the MIP and NLP versions of the model are depicted in Figure 74. The NLP problem uses

the MIP solution as the starting point. Notice that these are the solutions obtained when the model is run with the single factor curve using the learning-by-doing progress ratios from Table 1. That is, as if the learning-by-searching progress ratios were set to one. They, of course, differ from the values that would be obtained if progress ratios were derived from estimates of a single-factor learning curve using the same data.

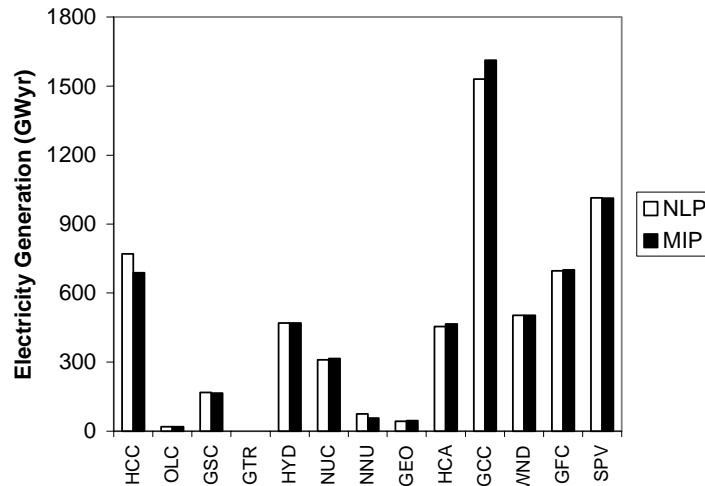


Figure 74. Comparison of the global electricity generation in 2050. Single-factor learning curve. NLP and MIP solutions.

For the case with exogenously specified R&D expenditures per technology, both MIP and NLP formulations were tested. The solution of the two-factor MIP version of the model was used as the starting point for the NLP problem⁷². Results using the two-factor learning curve are presented in Figure 75 for the MIP formulation and Figure 76 for the NLP one. Although there is no appreciable difference in the MIP case, the effects of the consideration of R&D expenditures are noticeable in the NLP case, with a tendency to favour technologies with lower learning by searching progress ratios. In the NLP formulation it can be seen that the money assigned to solar PV is not enough to render it competitive, leaving the technology "locked-out" of the solution. On the other hand, spending on R&D provides an edge to the gas fuel cell and the gas combined-

⁷² Due to the non-linear, non-convex nature of the problem, solving the NLP version with conventional solvers (such as MINOS5, the one used here) enables only the identification of a local optimum. The MIP version provides a linear approximation of the non-convex objective function. For such approximation a global optimum can be identified. However, previous experiments (Kypreos and Barreto, 1998a) with the single-factor formulation of the learning curve have shown that if, when solving the NLP problem, the solution of the MIP one is used as a starting point it is possible in many cases to identify a better local optimum. A similar procedure is also followed here. The solution of the two-factor MIP problem with exogenous R&D expenditures is used as the starting point of the corresponding two-factor NLP problem. However, when R&D expenditures are endogenous, it was the solution of the single-factor MIP problem the one used as the starting point of the two-factor NLP problem, given that the two-factor NLMIP problem was not formulated. Such solution to the NLP re-started problem is the one reported here, when reference to NLP is made in the figures. However, the caveat should be made that there is no guarantee that such procedure is the most adequate for the two-factor NLP problem. This is particularly so for the formulation with endogenous R&D expenditures, because it is possible that using the single-factor MIP solution as initial point the model is forced to find a two-factor NLP solution in the "vicinity" of the single-factor MIP solution, which is not necessarily the best possible option. The issue should be explored more carefully in the future and alternatives procedures should be considered.

cycle turbine, which are able to increase their market share as compared to the single-factor situation.

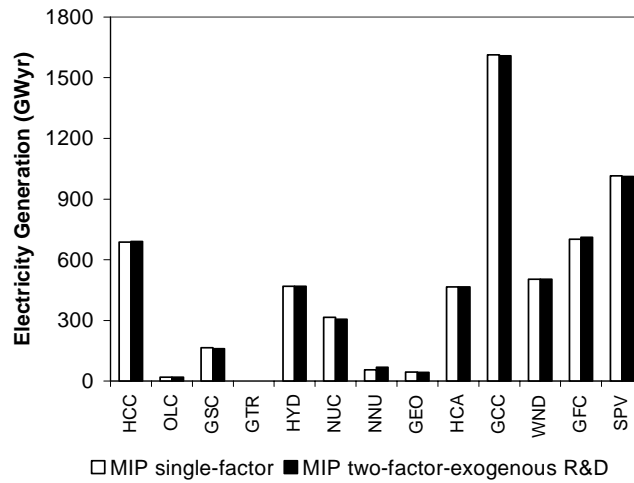


Figure 75. Comparison of global electricity generation in 2050 for two MIP solutions. Single-factor learning curve and two-factor learning curve with exogenous ARD.

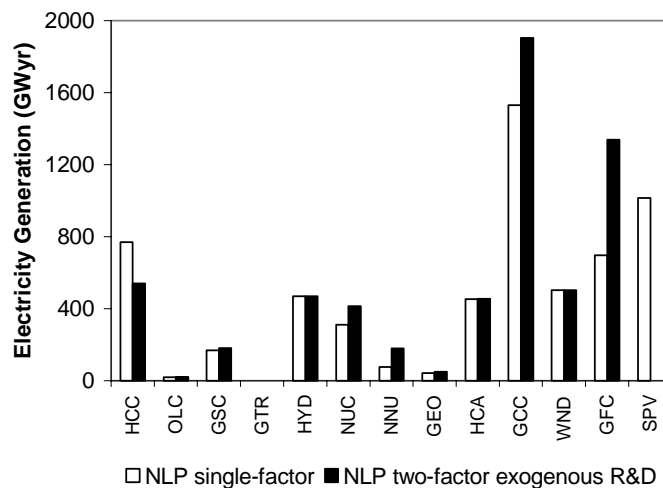


Figure 76. Comparison of global electricity generation in 2050. NLP solutions. Single-factor learning curve and two-factor learning curve with exogenous ARD.

Although this formulation provides insights into the effects of assigning a pre-specified amount of R&D funds to a given technology, it does not shed any light on the issue of what would be an "optimal" allocation of the R&D funds. Some insights on that matter, however, can be obtained by letting the model choose which fraction of a given annual R&D budget should each of the competing learning technologies receive. In this case, where a global R&D budget is specified, only the NLP formulation was applied. As mentioned before, the solution of the standard single-factor curve MIP problem was used as the starting point for the two-factor curve NLP one. The corresponding R&D

expenditures per technology found by the NLP model⁷³ are shown in Figure 77. Figure 78 presents the relative share of the R&D budget allocated to each learning technology.

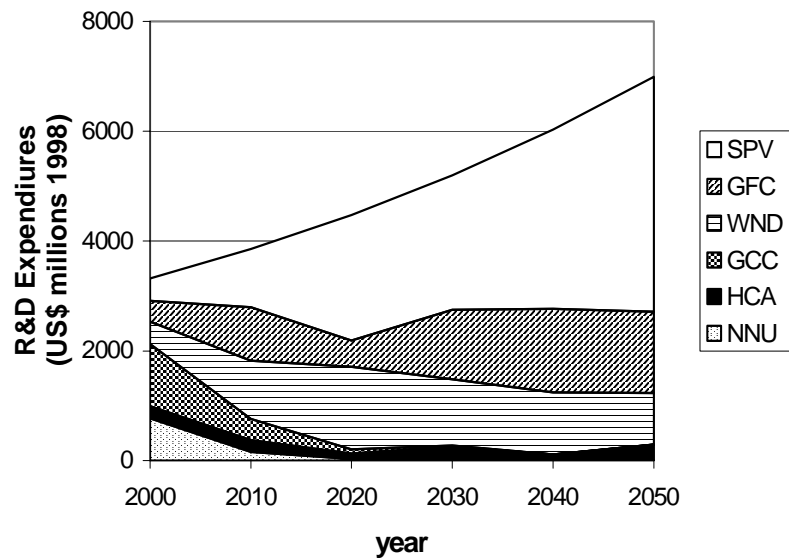


Figure 77. *R&D expenditures per technology. Cumulative R&D formulation. Endogenous ARD.*

Solar PV, the technology with the lowest learning-by-doing (lbd) progress ratio and one of the lowest learning-by-searching (lbs) ones, dominates the allocation of R&D resources⁷⁴. The gas fuel cell and the wind turbine also receive significant fractions of the R&D funds. R&D investments in the gas combined cycle turbine, that received the highest amount of resources in the first period, decline and disappear. The clean coal technology, having a very high learning-by-searching progress ratio but a relatively attractive learning-by-doing one, receives a small amount of the R&D money. On the other hand, the new nuclear power plant with both the highest lbd and lbs progress ratios results completely unattractive and R&D investments on it decay along the minimum growth constraint and disappear. Thus, as expected, the technologies with the lowest learning-by-searching progress ratios appear to be more attractive for expending R&D resources. However, other factors such as the learning-by-doing progress ratio, the maximum growth rates allowed and the presence or absence of a constraint on emissions, which may force low-carbon technologies into the solution, play also an important role.

⁷³ In this exercise, besides the maximum and minimum growth constraints for the $ARD_{te,t}$ variables, no additional conditions are imposed on the R&D expenditures, so the model can allocate the budget freely. For more elaborated exercises, however, it could be necessary to consider more sophisticated allocation rules, for instance taking into account that, as technologies mature, the importance of R&D expenditures as a cost reduction factor may diminish as market experience becomes the main mechanism of progress.

⁷⁴ This could be regarded as an example of the possibility of having a sort of "lock-in" of the R&D spending in the model. The model may try to continue to assign R&D money to a technology because it makes its cost cheaper and cheaper.

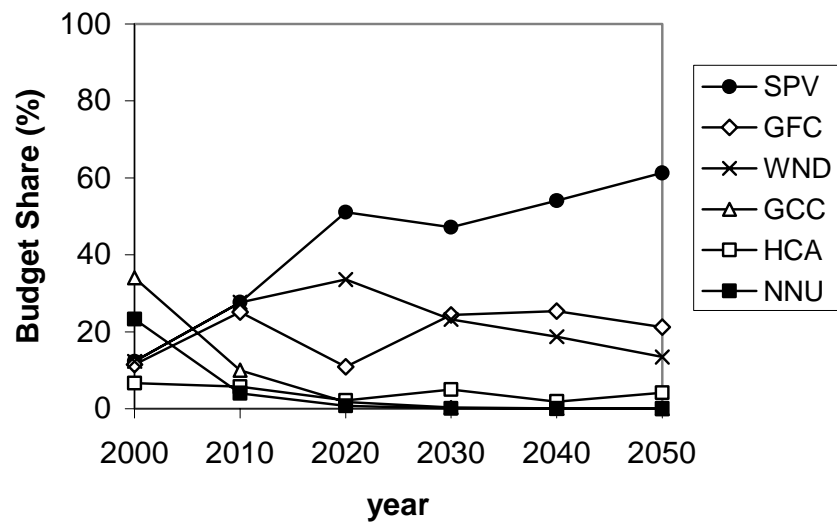


Figure 78. Share of the global annual R&D budget allocated to each learning technology. Cumulative R&D formulation. Endogenous ARD.

The generation mix in 2050 for the NLP case with endogenous allocation of R&D resources is shown in Figure 79, compared to the single-factor situation. The R&D spending contributes to slightly increase the output of several technologies such as the gas combined cycle and the gas fuel cell.

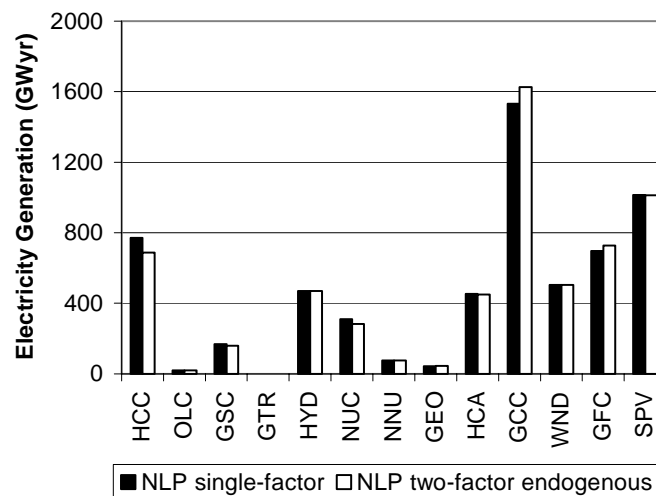


Figure 79. Comparison of global electricity generation in 2050. NLP solution. Single-factor and two-factor learning curves, the latter with endogenous ARD.

An interesting feature of this formulation is that the allocation of R&D resources occurs endogenously, guided by the two-factor learning curve and being influenced by the specific set-up of the model and the particular developments in a given scenario. The coupling of the R&D expenditures with the learning-by-doing mechanism and the other variables in the model, made possible here by its specification as an endogenous contributing factor to the cost reduction, is important because it helps to reflect in the model the fact that market investments and expectations play an important role in whether or not R&D money would be expended on a given technology.

In order to illustrate the factors influencing the R&D budget allocation, a sensitivity run was made where the installed capacity of solar PV is enabled to experience a lower growth. A maximum growth rate of 10% per year, instead of the 15% per year used so far, is specified. As already discussed, the maximum growth rate is one of the decisive factors in setting in motion (or not) the learning-by-doing mechanism. Here, with a lower growth rate, the technology does not have the same potential for learning along time and its competitiveness is strongly affected (see Figure 6). It becomes a marginal technology. Correspondingly, the market shares of the gas combined cycle and the gas fuel cell are substantially increased. Also, and in consequence, it becomes less attractive to invest on R&D for solar PV and the allocation of the R&D budget changes accordingly. In the new situation the gas fuel cell and the wind turbine dominate the allocation of the funds. Solar PV still receives a fraction, but it is significantly lower. The comparison of the electricity generation in 2050 for the original and the sensitivity cases is presented in Figure 80 and the corresponding relative allocation of the annual budget in shown in Figure 81.

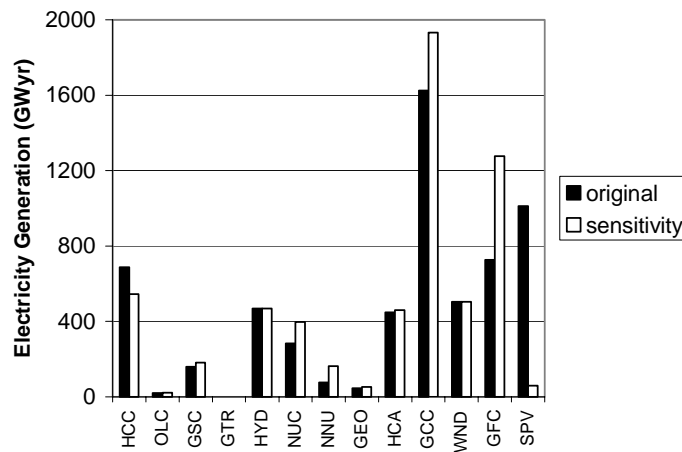


Figure 80. Comparison of global electricity generation in 2050. NLP solution. Original and sensitivity case. Endogenous R&D expenditures.

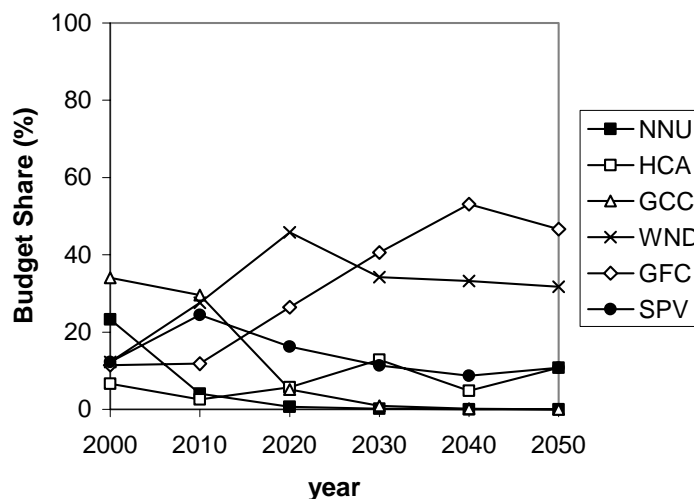


Figure 81. Share of the total annual R&D budget allocated to each learning technology. Sensitivity case.

7.5 Other formulation of the R&D budget constraint

The formulation of the R&D budget constraint used so far (equality) forces the model to spend the money available in a given period. In this section, the response of the model is examined when the constraint is formulated as:

$$GRD_t \geq \sum_{te \in TEG} ARD_{te,t} \quad (41)$$

In such way the model may decide whether to expend the assigned R&D budget or not. Figure 82 shows the fraction of the total available budget that it is assigned to the set of learning technologies. The budget is not fully allocated, although the favoured technologies are not significantly different (as compared to Figure 78). After being all the money allocated in the first period (due to the initial condition imposed), the amount of money decays in the second period, declining to the minimum bound imposed by the minimum growth constraints of the individual R&D expenditures (approx. 20% per period) and initiates an upward trend afterwards declining again only at the end of the horizon. Figure 83 presents the R&D expenditures per technology and Figure 84 shows their relative allocation under these conditions.

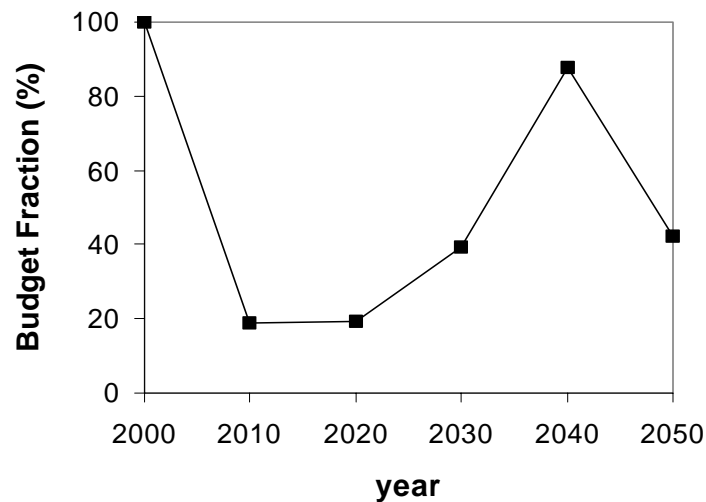


Figure 82. *Allocated fraction of the budget. R&D budget constraint as inequality.*

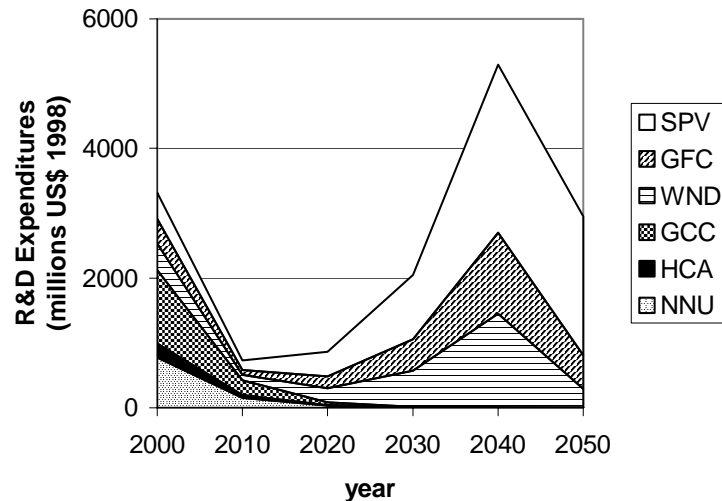


Figure 83. *R&D expenditures per technology. Cumulative R&D formulation. Endogenous R&D expenditures. R&D budget constraint formulated as inequality.*

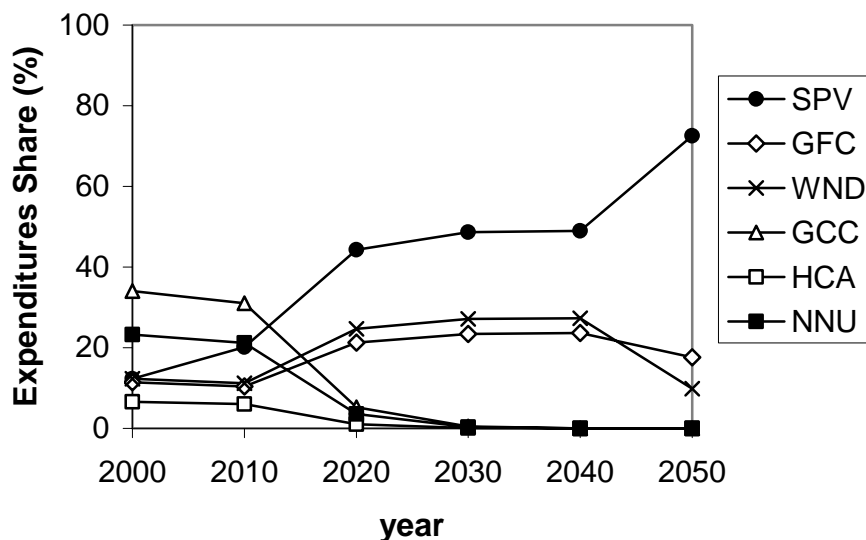


Figure 84. *Share of the total annual R&D expenditures allocated to each learning technology. Cumulative R&D formulation. Formulation of R&D budget constraint as an inequality.*

7.6 The knowledge stock formulation

An important issue concerns the variable used to represent the knowledge accumulated through R&D processes. Instead of having the cumulative R&D expenditures used here so far, the use of a "knowledge stock" function has been proposed in the literature (Griliches, 1984, 1995, Watanabe, 1995, 1999), in order to take into account several aspects of the R&D process. On the one hand, it takes time to conduct R&D projects as well as to apply the results to the production process. Thus, there are time lags between the actual R&D expenditures and the corresponding effects on productivity. On the other hand, past R&D investments depreciate and become obsolete (Griliches, 1995).

Thus, in order to capture those characteristics, a general "knowledge stock" function can be formulated in terms of current and past R&D expenditures, which may depreciate in time.

Here, the recursive expression for "knowledge stock" applied by Watanabe (1995, 1999) is implemented. Such formulation assumes that knowledge depreciates in time and that only the R&D expenditures performed n years before contribute to the current knowledge stock. That is, a constant lag is assumed between the time at which R&D spending takes place and the time at which its results materialise and become part of the knowledge stock. The original expression is given on a year-by-year basis. The knowledge stock in the year y (K_y) is expressed as the summation of the (depreciated) stock of the previous year ($y-1$) and the (n years) lagged R&D expenditures:

$$K_y = (1 - \delta) * K_{y-1} + ARD_{y-n} \quad (42)$$

Where:

K_y : Knowledge stock in year y

K_{y-1} : Knowledge stock in year $y-1$

δ : Annual depreciation rate

ARD_{y-n} : Lagged annual R&D expenditures per technology

n : Lag in years between R&D expenditures and knowledge stock.

The "knowledge stock" appears to be a more suitable form of measuring the R&D contribution than simply cumulating R&D expenditures on time. Of course, when no depreciation or lags are assumed, the knowledge stock is reduced to cumulative R&D expenditures. Tests performed with time series from energy technologies indicate that its application appears to improve the statistical estimates of the two-factor learning curves as compared to the case where cumulative R&D expenditures are specified (Criqui et al., 2000). However, it also introduces the problem of obtaining sensible assumptions or estimations of the relevant lag structure and the depreciation rate. Although some case studies are available (Watanabe, 1999), estimations of those parameters in the case of energy technologies must still be developed. In the meantime sensitivity analyses can be applied to assess their effect. For such task the ERIS model with the two-factor learning curve may constitute a valuable tool.

The above is an annual expression, but the length of the period in the ERIS model is normally bigger than one year and values are assigned to the variables on a period-by-period basis. Therefore, in order to be consistent, it is necessary to compute the knowledge stock for each period in the model, taking into account the year-by-year formulation above.

For such purpose it is assumed that annual R&D expenditures per technology are constant along the period, as it is the case with the other variables in the model. The value of the knowledge stock for a given period (computed at the end of the period) is obtained using the corresponding ARD series for the current and the previous period as:

$$K_t = K_{t-1} * (1 - \delta)^{\Delta_t} + ARD_t * \sum_{\tau=0}^{\Delta_t - rdlag - 1} (1 - \delta)^\tau + (1 - \delta)^{\Delta_t - rdlag} * ARD_{t-1} * \sum_{\tau=0}^{rdlag - 1} (1 - \delta)^\tau \quad (43)$$

This expression provides a computation of the knowledge stock that is consistent with the above year-by-year formulation, under the assumption that the R&D expenditures series remains constant along each period.

For the first period the computation must include the lagged annual historical R&D expenditures values (*ardpast*) and thus it becomes:

$$K_t = dknow * (1 - \delta)^{\Delta_t} + ARD_t * \sum_{\tau=0}^{\Delta_t - rdlag - 1} (1 - \delta)^\tau + (1 - \delta)^{\Delta_t - rdlag} * \left[\sum_{\tau=0}^{rdlag-1} (1 - \delta)^\tau * ardpast_\tau \right] \quad (44)$$

Where the $ardpast_\tau$ values are given backwards with respect to the specification of the initial knowledge stock (*dknow*). That is, $ardpast_0$ corresponds to the R&D expenditures in the same year for which *dknow* is given, $ardpast_1$ are those of the previous year etc. The equations above assume that $rdlag < \text{period length } (\Delta_t)$.

The computation is done at the end of each period because the cumulative capacity for a given period is computed as the one in the previous one plus the investments taking place in the current one and both values should be consistent in order to be introduced in the learning curve⁷⁵.

To illustrate the influence of the depreciation rate and the R&D lag in the knowledge stock, Figure 85 and Figure 86 present the behaviour of a hypothetical knowledge stock function when those parameters are modified. For simplicity the knowledge stock is given in relative terms to the value of the first period, which is assigned to 1. A "stair-case" time series is assumed for the annual R&D expenditures (*ARD*, also shown in the figures). The *ARD* series starts with a unitary value and increases its value in one unit every ten years (as to simulate a possible pattern in the model). Figure 85 presents the effect of different depreciation rates, ranging from no depreciation up to 15% per year. The lag parameter is set to 4 years. As expected, for the same flow of R&D expenditures a lower depreciation rate produces higher values of knowledge stock.

⁷⁵ In the ERIS model it is assumed that the period named as "2000" comprises the years from 2001 to 2010, the period "2010" goes from 2011-2020 etc. Thus, for the purposes of knowledge stock calculation the variable *ARD(2000)* will be the annual R&D expenditures for 2001-2010 and the variable *KNOW(2000)* is the corresponding knowledge stock at the end of the period.

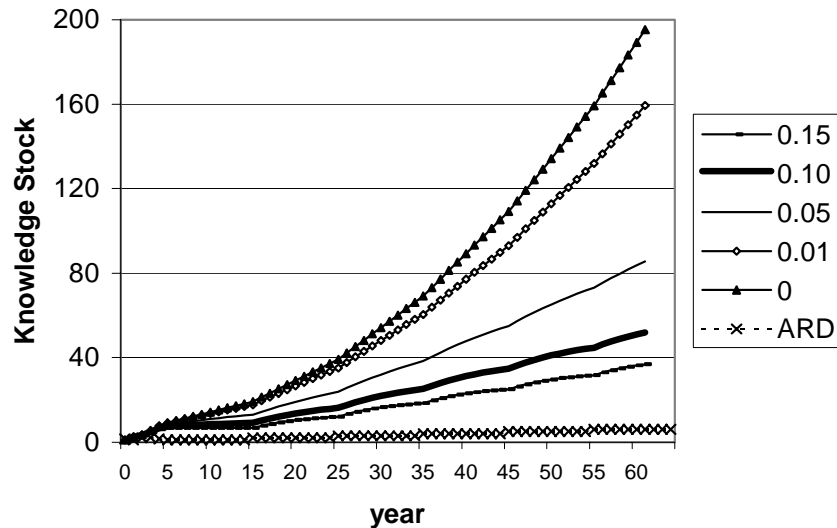


Figure 85. Knowledge stock. Different depreciation rates.

Figure 86 shows the effects of modifying the lag between R&D expenditures and knowledge stock, while keeping the depreciation rate constant to 5% per year. A lower lag, that is, a faster incorporation of R&D results into productivity gains, allows a faster growth of the knowledge stock. However, variation of the lag parameter produces less significant changes than that of the depreciation rate.

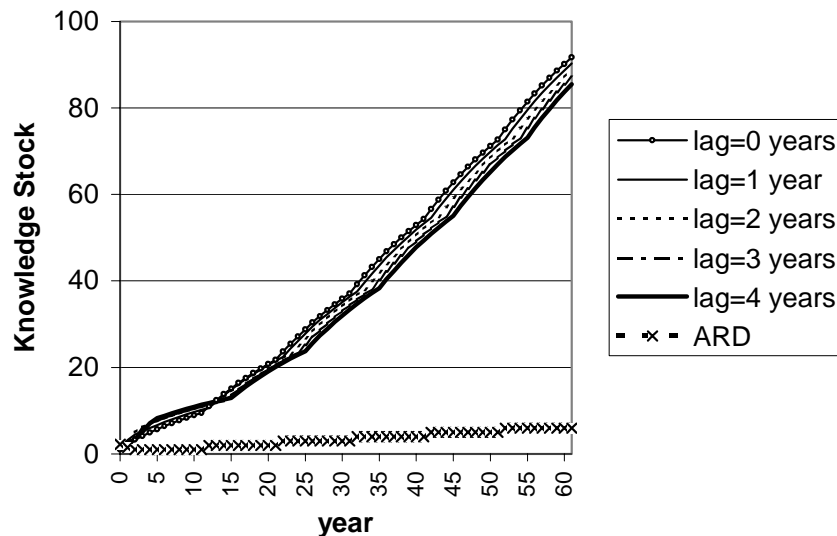


Figure 86. Knowledge stock. Different R&D lags.

When the knowledge stock is incorporated the two-factor learning curve is transformed into:

$$SC_{te,t}(C, K) = a * C_{te,t}^{-b} * K_{te,t}^{-c} \quad (45)$$

It must be noticed that the inclusion of the knowledge stock in the curve provides the model with a mechanism of "forgetting-by-not-doing", although only for the R&D learning channel. With such mechanism, leaving aside the effects of cumulative capacity, if no R&D expenditures are made in a given technology the knowledge stock

will depreciate and, therefore, the specific costs of the technology will increase. This is an interesting feature but it should be handled carefully. The question arises how much should the forgetting process be allowed to occur. Also, it would be interesting to examine whether (and how) a similar mechanism should be incorporated also in the cumulative capacity factor.

Some illustrative tests have been carried out with this modified formulation. The analysis was concentrated in examining the effects of different values of the rate of depreciation of the knowledge stock (from 0 to 15% per annum), ignoring for the time being those of the R&D retards. As a simplification, no R&D lag was assumed and the same depreciation rate is applied to all learning technologies. The R&D budget constraint is formulated as equality first and then as an inequality.

Due to the lack of available estimates of two-factor learning curves using knowledge stock for the learning technologies applied here⁷⁶, additional assumptions were necessary. The *lbd* and *lbs* progress ratios are the same as the ones used previously with the cumulative R&D expenditures formulation and the initial knowledge stocks (*dknow*) are considered equal to the initial cumulative R&D expenditures.

At first, the situation with the R&D budget constraint formulated as equality is examined. Figure 87 presents the relative allocation of the budget shares. Figure 88 gives a comparison of the share of each of the learning technologies as the depreciation rate increases. Solar PV continues to be the most attractive technology across the range of rates evaluated. However, its share of the R&D budget decreases as the depreciation rate is increased. The same occurs to the gas fuel cell and the wind turbine. On the other hand, the new nuclear and advanced coal power plants still result unattractive, although the amount of R&D expenditures tends to increase. In addition, the R&D investments on the gas combined cycle turbine experience a much slower decrease.

⁷⁶ Some preliminary estimates of two-factor learning curves using knowledge stock for solar PV and wind turbines have been presented in Criqui et al. (2000).

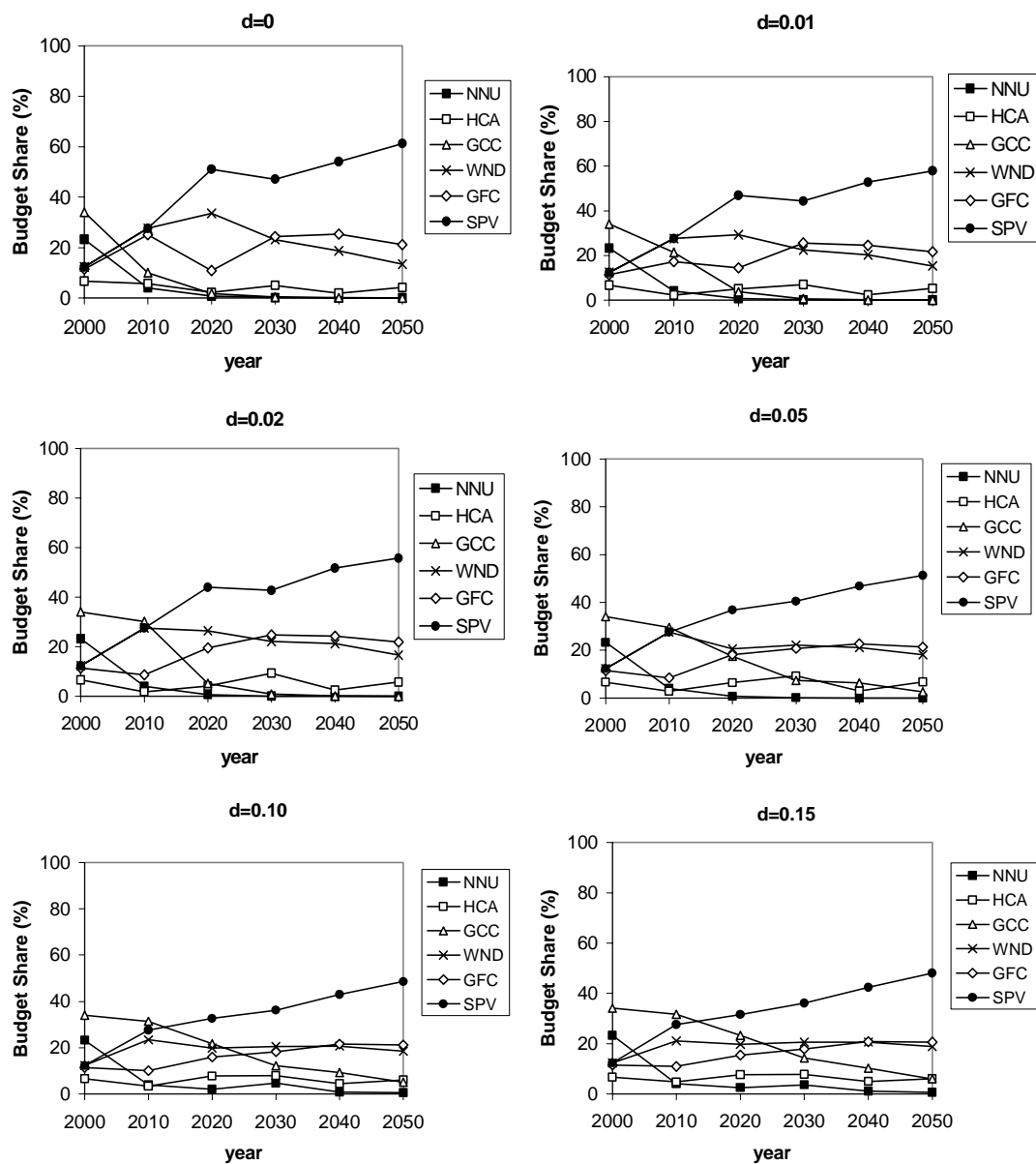


Figure 87. Time evolution of the R&D budget shares. Knowledge stock formulation. Different depreciation rates. R&D budget constraint as an equality.

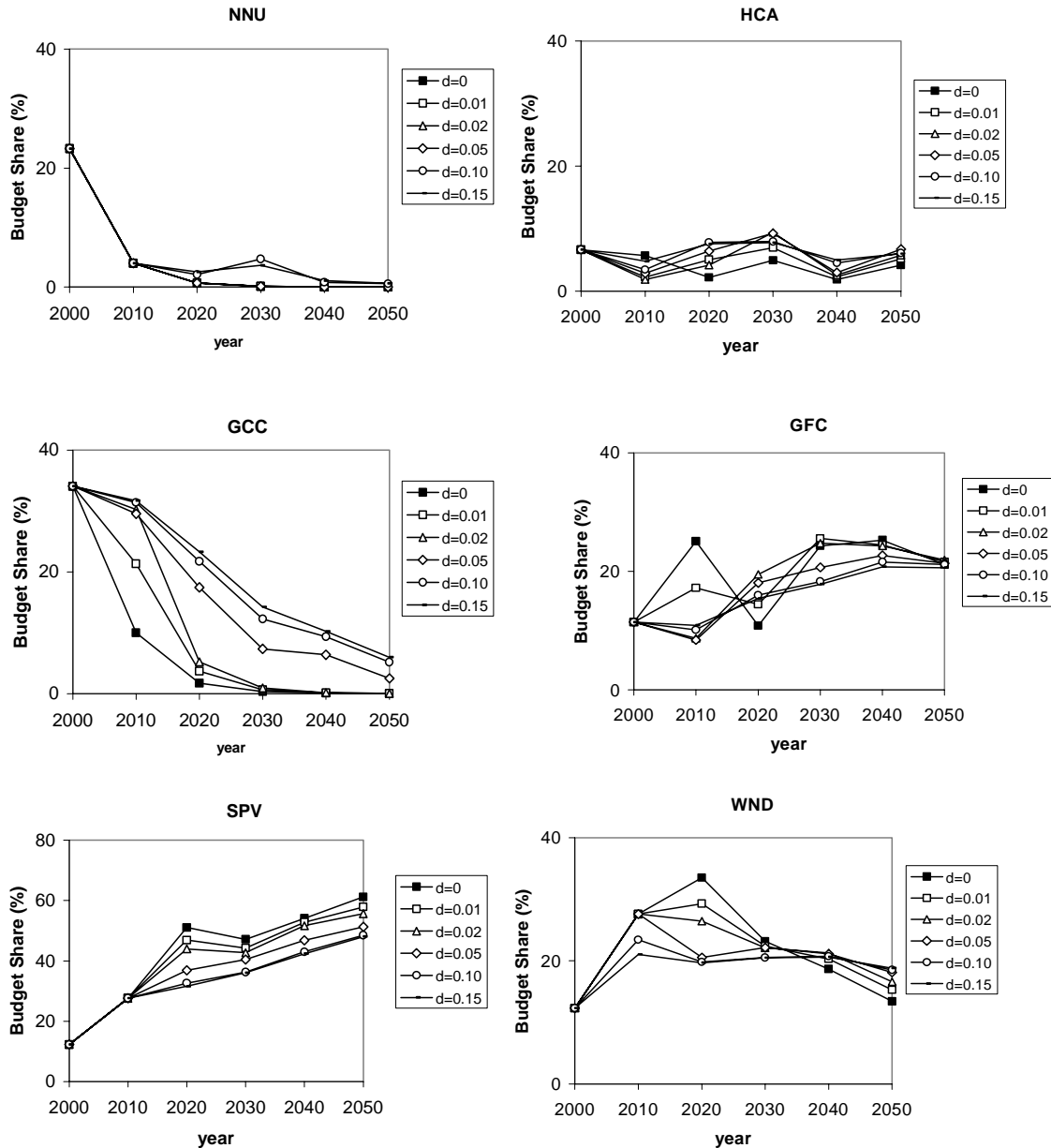


Figure 88. Share of R&D budget per learning technology. Different depreciation rates. R&D budget constraint as an equality.

The introduction of depreciation of the knowledge stock alters the dynamics of allocation of R&D funds and reduces the effectiveness of R&D as a cost reduction factor. The cost trends of a given technology will be more or less affected by a higher depreciation rate depending on how strong the R&D factor contributes to the cost reduction⁷⁷, how attractive are its learning-by-doing and learning-by-searching progress ratios as compared to other technologies, which is the size of the R&D budget and how cost-competitive is the technology already.

⁷⁷ This depends on the relative weight of the learning-by-searching elasticity respect to the learning-by-doing one, but also on other factors such as the size of the R&D budget and the maximum growth rates of both capacity and R&D expenditures.

In the particular case illustrated here, as the depreciation rate was increased, the model shifted towards investing more R&D money to counteract the effect of such higher depreciation in the cost of an already very competitive and widely deployed technology (the gas combined-cycle), which also has a very attractive learning-by-doing elasticity, despite the fact that its learning-by-searching elasticity is very low. In consequence, given that a limited R&D budget is available, it diminished the support of much more expensive but promising technologies such as solar PV or the gas fuel cell, which possess a more attractive learning-by-searching elasticity. This is an interesting insight of how the model may respond in the presence of a forgetting factor. Still, a more profound examination of the implications of this formulation in the model results is necessary.

Figure 89 presents the electricity generation in the year 2050 under the different depreciation rates. Being a constrained scenario, no significant variations in the technology mix appear. Nonetheless, some technologies still alter their outputs. In particular, the gas combined-cycle diminishes its electricity generation as the depreciation rate is increased. Despite the injection of R&D money, the depreciation makes it slightly less competitive. The increasing rate also affects the new nuclear power plant, whose output declines substantially. Correspondingly, other technologies are able to increment their share of the market, in particular the advanced and conventional coal plants and the conventional nuclear one.

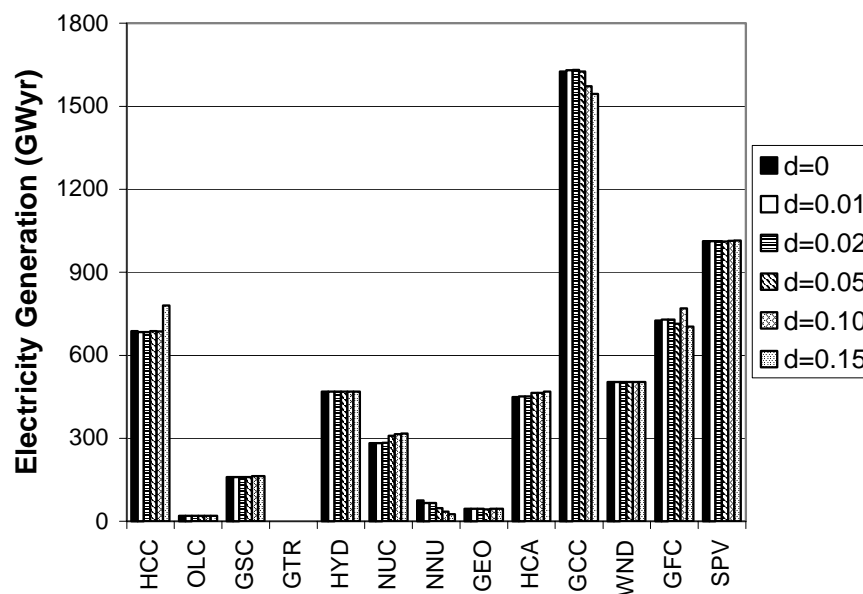


Figure 89. Electricity generation mix in 2050. Different R&D knowledge depreciation rates.

As seen previously, the formulation of the R&D budget constraint affects the results. Thus, in order to examine the impact of the depreciation rate on the total amount of R&D funds spent, the sensitivity analysis was repeated with the inequality formulation, leaving the model free to decide whether to invest or not in R&D activities. Results are presented in Figure 90 to Figure 92.

Figure 90 presents the total amount of R&D expenditures for different values of the depreciation rate, expressed as a fraction of the budget available in each period. It can be seen that, although still the budget is not fully allocated, with an increasing depreciation rate there is a tendency to augment the fraction of budget that is spent. At a higher depreciation rate, more money is necessary to produce the same results in terms of cost reductions and, as before, the model decides to invest more money in order to counteract the "forgetting-by-not-doing" effect introduced by the depreciation in competitive technologies.

This is also an interesting behaviour because, in principle, a higher depreciation rate should reduce the attractiveness of investing in R&D. For high depreciation rates the model could consider more beneficial either to invest more in capacity, given that such factor does not suffer depreciation, or simply not to invest in R&D. However, an additional counterbalancing factor intervenes here. No R&D investments would mean "forgetting" and this would traduce into increasing costs in the model. Thus, there is an incentive to invest in R&D to counteract the "forgetting" effect. Although a definite interpretation of this fact is not possible here, one could probably expect the increasing tendency on the expenditures to last only as long as the model considers the technology attractive enough. These interactions deserve further investigation.

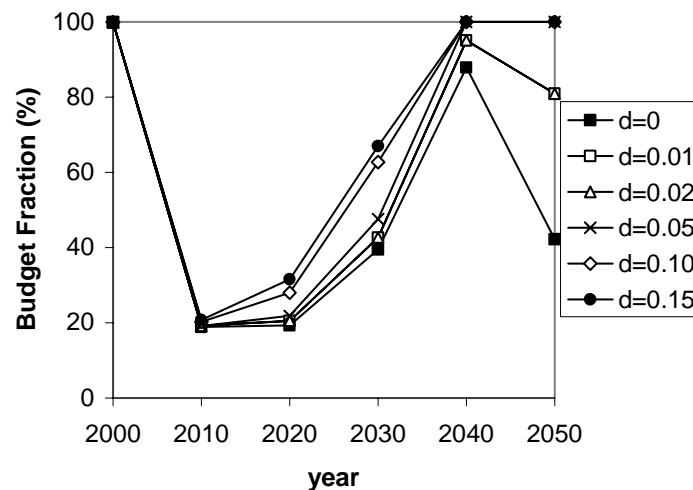


Figure 90. *Expended fraction of the total R&D budget. Different depreciation rates. R&D budget as an inequality constraint.*

Figure 91 presents the relative allocation of the total R&D expenditures among the learning technologies. Figure 92 presents the changes of the share of each technology as the depreciation rate is modified. To distinguish them from the previous case, the label expenditures share is used in the figures, as to denote that not necessarily the full budget is allocated. As before, the relative share of solar PV diminishes with increasing depreciation rate. However, the technology continues to be the most attractive. Investments on the gas fuel cell and the wind turbine also decrease. The gas combined cycle experiences a much slower decline. The advanced coal technology gains share although is still unattractive and the new nuclear power plant remains the least attractive one.

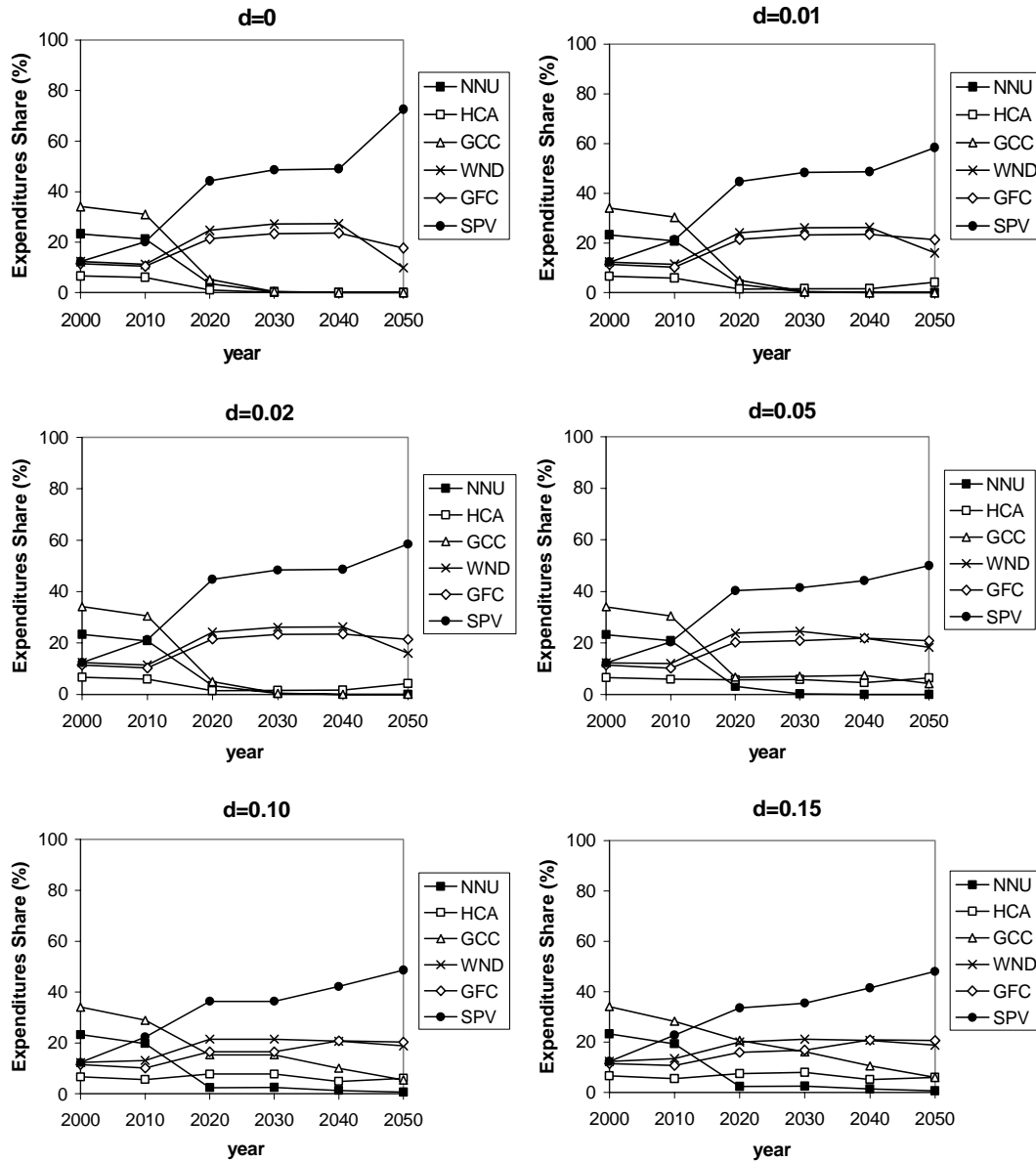


Figure 91. Time evolution of the expenditures share. Knowledge stock formulation. Different depreciation rates. R&D budget as inequality constraint.

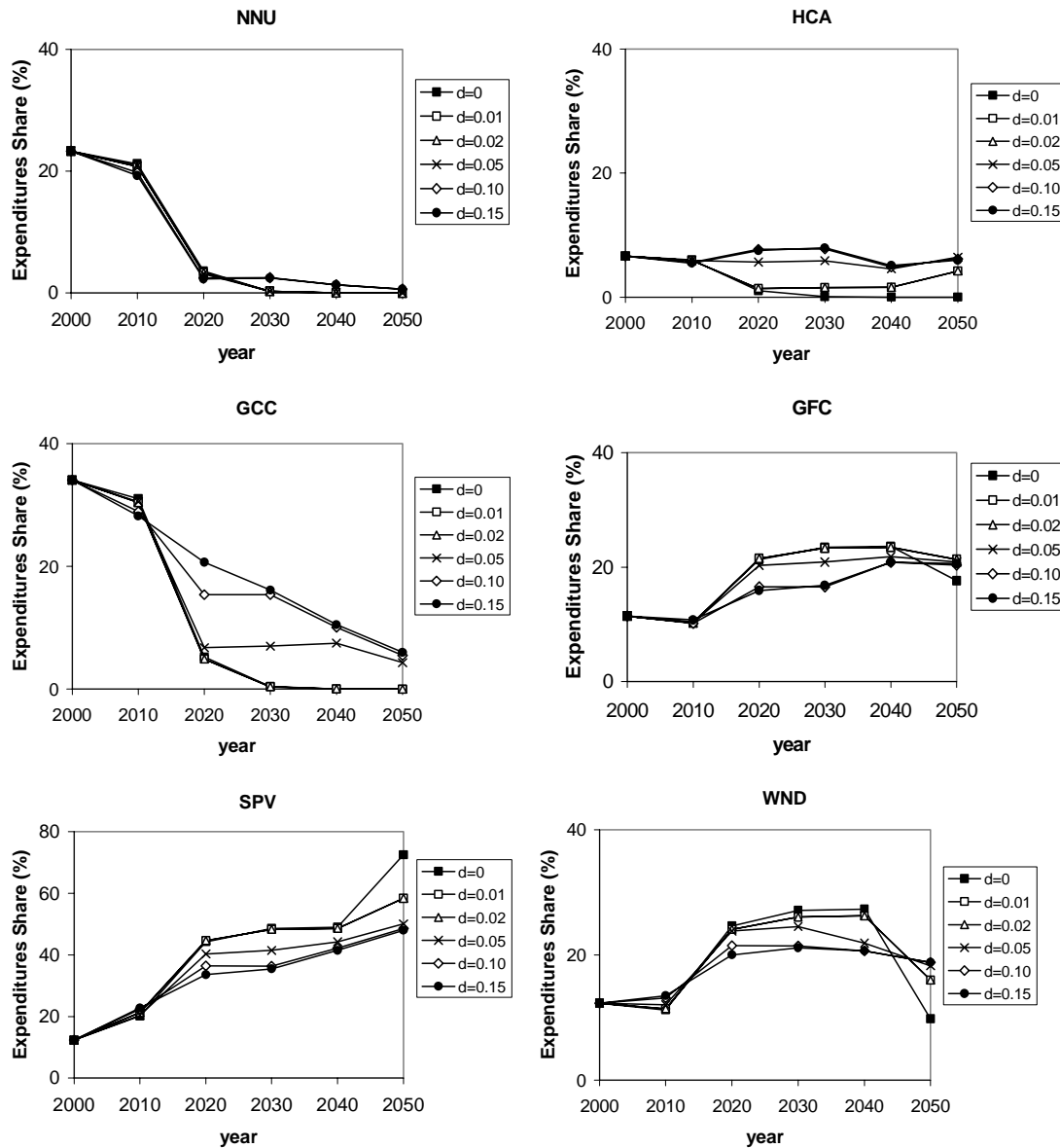


Figure 92. Share of total R&D expenditures per learning technology. Different depreciation rates. R&D budget as an inequality constraint.

7.7 Final remarks

A two-factor learning curve is implemented in the ERIS model, allowing the consideration of the effects of cumulative R&D expenditures together with those of cumulative capacity in the cost reduction of learning technologies.

Some preliminary illustrative results are presented for different specifications of R&D expenditures per technology. In the first specification, exogenous time-dependent R&D expenditures per technology are given. Such formulation may be useful to examine the effects of assigning a given amount of R&D resources to a given technology, and could be helpful in determining how much R&D money should be necessary for a technology to become competitive under certain circumstances. However, allocation of R&D

resources is still externally given. In the second one, R&D expenditures are specified as an endogenous variable. A global R&D budget is provided and the model finds its optimal allocation among the different learning technologies. Such formulation is useful in defining the distribution of R&D resources among several competing technologies taking into account a number of intervening factors. The endogenous specification of R&D expenditures and the use of the two-factor learning curve as the guiding allocation rule enable making the allocation of R&D resources dependent upon other parameters of the model.

In addition, in order to reflect the fact that time lags and depreciation occur in R&D processes, a knowledge stock function is introduced in the place of cumulative R&D expenditures. The knowledge stock formulation allows considering the retards between R&D spending and productivity gains (in this case cost reductions) and that past R&D investments depreciate and become obsolete. Through the depreciation rate an element of "forgetting-by-not-doing" is introduced in the R&D component of the learning process. It is important for the modeller to bear in mind the connotations of such "forgetting-by-not-doing" feature. It implies that, leaving aside the effects of accumulating capacity, if no efforts on R&D are made on a given technology, its investment costs will increase. However, it still has to be discussed whether this constitutes a realistic representation of the process, and to which extent the forgetting process should be allowed to occur. Also, the possibility of introducing such "forgetting-by-not-doing" characteristic in the cumulative capacity mechanism must be examined carefully.

The approach depends critically on obtaining a statistically meaningful estimation of separate learning-by-doing and learning-by-searching indexes. Problems regarding the quality of the underlying data and the estimation itself remain to be solved⁷⁸. Also, assumptions regarding the amount of R&D spending must be reviewed carefully in order to avoid excessive, unrealistic cost reductions. Nonetheless, this constitutes an important first step towards the incorporation of mechanisms to reflect the effects of R&D efforts in the technological progress of energy technologies in the ERIS model. Possible drawbacks of this implementation should be analysed more carefully and alternative approaches should be explored.

Further work should be devoted to a more elaborated representation of the process of allocation of R&D resources. If possible, the contributions of public and private actors should be differentiated. Also, the incorporation of stylised considerations concerning the influence of the technology's life cycle in the relative contributions of market deployment and R&D efforts could be explored. For instance, although here both mechanisms have been acting simultaneously for all the learning technologies, one should also consider situations where knowledge can be accumulated on a given technology through R&D before capacity deployment takes place. In addition, although the formulation applied here treated both contributing factors as substitutes, some degree of complementarity between them could very likely exist. The examination of

⁷⁸ For instance, multicollinearity, that is high correlation between the two explicative variables (cumulative capacity and cumulative R&D or knowledge stock), arises. One of the reasons for such high multicollinearity can be the fact that each of those variables may respond to changes in the other. Increases in the sales volume, for example, may trigger a higher R&D spending by producing firms, as to ensure the technology remains competitive in the marketplace.

their substitutability and/or complementarity characteristics and how they can alter the basic formulation given here is an aspect that deserves more profound analysis.

The incorporation of R&D aspects in ERIS and other energy models is important for the examination of energy technology policies. Model analyses may help to undertake more systematic efforts and gain insights as to how to invest scarce R&D resources more effectively and how to conform robust and flexible portfolios of promising new energy supply and demand technologies whose development should be supported.

The introduction of this second factor into the learning curve enables an improved and more comprehensive (though, of course, not complete or definitive) treatment of the factors involved in the cost reduction and allows the modeller to take into account the effects of R&D in energy technology policy in a more direct way. Traditionally, such effects have been modelled in an exogenous way. For instance, awareness of actual R&D spending, or consideration of future plans to increase it, could drive to more optimistic considerations regarding cost and efficiency for a particular technology. Also, when applying the single factor learning curve, R&D could be reflected as a factor influencing the starting point of the learning curve or the corresponding learning index (see, for instance, Seebregts et al., 1998). Thus, its explicit incorporation in the learning curve and endogenous formulation in the model provide more "degrees of freedom" as to the way its impact and related policy questions may be addressed.

However, increased "degrees of freedom" may very likely imply increased data requirements, and, in the absence of reliable data, they will drive to a mounting number of assumptions. Although this certainly will pose difficulties, it should not be a discouraging point. The availability of a sound framework highlights the need to collect the corresponding data and, using for instance case studies, evaluate the missing variables. This has been already made relevant in the discussions concerning the standard learning curve and can be made extensive here. The curve works as a strategic tool to produce useful insights regarding RD&D and energy technology policies and provides a guideline to conduct case studies (Wene, 2000). Thus, the concept of the two-factor learning curve points out the need of evaluating the effects of energy R&D investments within the context of technological learning.

However, it is still early to define whether the two-factor learning curve will prove (or not) a convenient aggregate model adequately supported by the empirical evidence. Nonetheless, it must be understood as a helpful step towards the development of a more consistent representation of the technological learning process, where both market deployment and R&D efforts contribute to progress and interact with each other and other model parameters in a common framework.

8. Post-Kyoto analysis with a compact global energy system MARKAL model

In this chapter complementary analyses of the structure of the global electricity generation system are presented using a multi-regional "bottom-up" MARKAL model of the global energy system⁷⁹. Changes in the energy system, mitigation costs and CO₂-permits trade patterns are examined when a Kyoto-like CO₂ constraint is imposed on the energy system. Also, the effects of altering the scale of the learning process, already highlighted in a previous chapter, are studied and the concept of learning spillover coefficients is outlined. Emphasis is given to the interaction between the emissions' trading and learning mechanisms, which is illustrated with the deployment of learning electricity generation technologies under different circumstances.

8.1 Introduction

A compact multi-regional energy system MARKAL model has been developed on the basis of the IIASA databases of the MESSAGE model⁸⁰. Five regions have been considered. Two regions represent industrialised countries: North America (NAM) and the rest of the OECD (OOECD). One region brings together the economies-in-transition in the Former Soviet Union and Eastern Europe (EEFSU). Two additional regions portray the developing world: One of them groups the developing countries in Asia (ASIA) and the other comprises Latin America, Africa and the Middle East (LAFM). The regions correspond to aggregates of the eleven regions applied in IIASA-WEC (1995, 1998). The end-use demands as well as potentials for fossil fuels and renewable resources correspond to the SRES-B2 storyline characterisation carried out with the MESSAGE model (IPCC, 2000, Riahi and Roehrl, 2000), which is a scenario of gradual developments in population, economic growth and energy requirements, and a slow but progressive convergence of per capita income differences between developed and developing regions. The description of the database is presented in Appendix 5. The time horizon of the model is 1990-2050 and a 5% discount rate has been used in all the calculations.

⁷⁹ The purpose of developing such a model has been to provide a broader platform for subsequent studies on technological learning using the MARKAL model and a more comprehensive treatment of the energy system such that additional insights can be obtained. Unfortunately, time constraints did not allow performing extensive analyses with it in the framework of this dissertation and here only some indicative analyses are presented. It remains, nonetheless, a basis for further work in the future. A number of enhancements are possible (e.g. implementation of multi-regional clusters of energy technologies, improvements in the modelling of end-use devices, more detailed treatment of the transportation sector, etc.).

⁸⁰ As a compact model had to be developed, not all the technologies included in the MESSAGE databases were included in the MARKAL model. Also, the number of regions and several modelling constraints are not the same as those applied in the MESSAGE framework. In addition, other pollutants, such as SO_x and NO_x, were not considered here. Moreover, the time horizon of the multi-regional MARKAL model here is only 1990-2050 while that of MESSAGE extends to 2100. Besides that, here a MARKAL model with inelastic demands is applied and in the SRES analysis a MESSAGE-MACRO application is made. Due to those and other reasons, the results should not be expected to match with those presented in SRES (2000) and/or Riahi and Roehrl (2000). Neither it is claimed that a consistent characterisation of the SRES-B2 storyline is provided here. However, within the limitations and scope of this work, it could be considered a plausible development of the energy system. Of course, any shortcomings of the analysis presented here remain the sole responsibility of the present author.

Although the MESSAGE databases were the main source of data, for the sake of comparability with the previous exercises the electricity generation technologies, and their technical and learning characteristics, used in chapter 6 maintained. The only changes made are the inclusion of (gas-based) cogeneration and biomass power plants and the exclusion of the geothermal option. As before, six electricity generation technologies are assumed to exhibit progress ratios lower than one and eight segments have been applied for the piece-wise approximation of their learning curves.

As in the previous chapters, the study conducted here still concentrates on the behaviour of the global electricity generation system, being learning technologies considered only in such sector, mainly because of constraints on the computational capability available. But, there are three important differences. First, the demand for electricity is now determined endogenously, as electricity may compete with other final energy carriers to satisfy the end-use energy needs in several sectors. So far, the demand for electricity had been specified exogenously. Second, CO₂ constraints are applied on the entire energy system and not only on the electricity sector as before. Thus, the model can choose cost-effective mitigation measures in any suitable energy chain. Third, the full-system model also allows a better treatment of the depletion of primary fossil resources, with the introduction of stepwise cumulative supply/cost curves in each region and the consideration of the different alternatives of fossil fuel consumption besides electricity generation. Also, trade of oil, gas and coal is allowed across regions. Thus, although with less geographical resolution, in this exercise an assessment of the role of new electricity technologies is provided within the context of the evolution of the full energy system⁸¹.

As before, Kyoto-like CO₂ constraints are imposed on the model and its response is examined. Results obtained with the MIP learning model are presented here. Mainly global trends are discussed and the attention is concentrated on electricity generation. Three main CO₂ scenarios have been considered. The first one is an unconstrained baseline scenario denominated "Reference" scenario (abbreviated Ref). In the second one, labelled Kyoto trend scenario, Annex I regions (i.e. NAM, OECD, EFFSU) are compelled to reach their Kyoto targets by 2010 and to follow, from this target, a linear reduction of 5% per decade until the end of the horizon. Such scenario is, of course, more demanding than the Kyoto-for-ever one commonly examined in the literature (e.g. Weyant, 1999). The third scenario is a Kyoto global trend, which assumes that non-Annex I regions (i.e. ASIA and LAFM) commit themselves to an emissions reduction of 5% per decade from their baseline values in 2030, while the Annex I regions face the same targets as in the Kyoto-trend. In the Kyoto-trend scenario four variants of emissions trading are contemplated. In the first one, no trade is allowed. In the second one, trade is allowed only between Annex I regions, starting in the year 2010. In the third one, non-Annex I regions join the trading system in 2030. In the fourth one, non-

⁸¹ An additional caveat is necessary here. Energy conservation measures have not been considered in the model. Also, highly aggregated end-use demand sectors are considered and a detailed modelling of all the technological alternatives at the end-use level was not undertaken, as mainly generic technologies were specified. In such respect, this analysis may neglect a number of cost-effective energy efficiency measures that can play a role in greenhouse gas mitigation strategies. Also, due to particular assumptions of the scenario depicted here regarding trends of penetration of final energy carriers, the flexibility of response of the model at the end use level may be reduced.

Annex I regions join trade of permits earlier, from the outset in 2010. In the Kyoto-global trend one, only the first, third and fourth trade modalities are applied. In order to avoid carbon leakage, in the constrained scenarios non-Annex I regions are bounded to their baseline emissions. That is, they are endowed to their reference emissions and, when allowed, they can trade any emission reductions below them.

Concerning the spatial scale of the learning process of the electricity generation technologies, the attention has been concentrated in a reference global learning scenario. For simplification it is assumed that all technologies exhibit the same spatial scale of learning. As a complement, an example illustrating the response of the model under different configurations of inter-regional learning spillover is also presented but only a restricted discussion is carried out. For such example, three additional scales of learning were considered, which represent a geographical fragmentation of the process compared to the global learning scenario: Annex I/non-Annex I, IND/EIT/DEV (industrialised, economies-in-transition and developing groups) and single-region learning domains.

8.2 Global learning

Initially, a reference situation assuming global learning for the electricity generation technologies is analysed. The discussion on costs of fulfilling the Kyoto-trend constraint is carried out only for this global learning scenario.

8.2.1 Reference scenario

At first, the unconstrained baseline case (Ref) is considered. In order to provide an appropriated context the structure of primary and final energy supplies are briefly examined first. The regional composition of primary and final energy consumption, as well as the market share of the different energy carriers in the global aggregate, are presented. Afterwards, the attention is turned to the evolution of electricity markets.

8.2.1.1 Primary energy consumption

Under this scenario, global primary energy consumption experiences a significant increase, growing at an average rate of 1.54% per year. It is still largely dominated by fossil fuels (see Figure 93). Both coal and natural gas experience a substantial growth, with gas becoming the predominant source by the end of the horizon. Growth of oil remains modest, but it still continues to hold a significant contribution. Non-fossil resources slowly gain market share⁸².

⁸² The contributions of hydropower and nuclear electricity and non-thermal uses of renewables were computed using the so-called direct equivalent method.

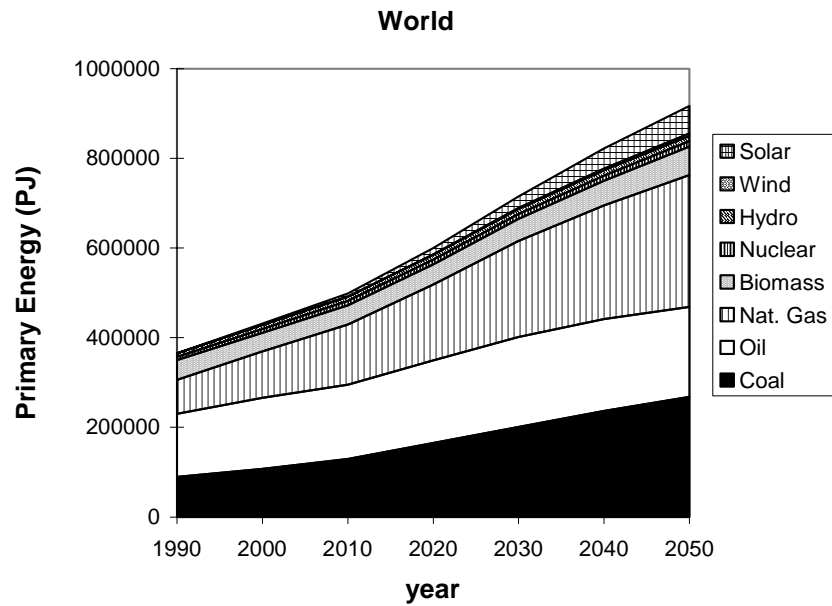


Figure 93. *Global primary energy consumption per energy carrier. Reference scenario.*

As for the regional participation in the primary energy consumption (see Figure 94), industrialised and economies-in-transition regions still experience some growth but the bulk of the increase in consumption takes place in developing regions, particularly in ASIA. In the OECD region, slow growth of the end-use demands combined with efficiency improvements in its energy system result in a very modest growth of their primary energy consumption up to 2030 and a decline afterwards.

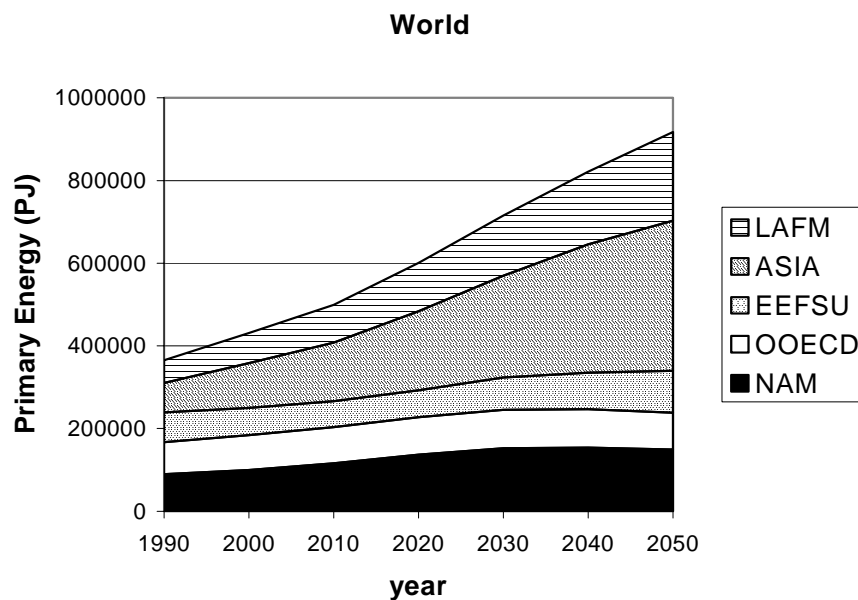


Figure 94. *Regionalised primary energy consumption. Reference scenario.*

Figure 95 presents the corresponding CO₂ emissions per region. A significant increase is evident. Emissions grow at an average rate of approximately 1.5% per annum for the period 1990-2050, becoming in 2050 2.5 times their value in 1990. As the centre of

gravity of energy consumption is displaced toward developing regions, also their weight in global emissions augments substantially. While in 1990 they constituted 30% of the total, in 2050 such fraction has risen to 63%. Specifically, developing ASIA becomes the most important emitter. On the other hand, emissions in the Annex I group follow a very moderate growth until 2030, stagnating in the subsequent period. In the OECD region, emissions decline after such year, reaching in 2050 lower levels than in 1990.

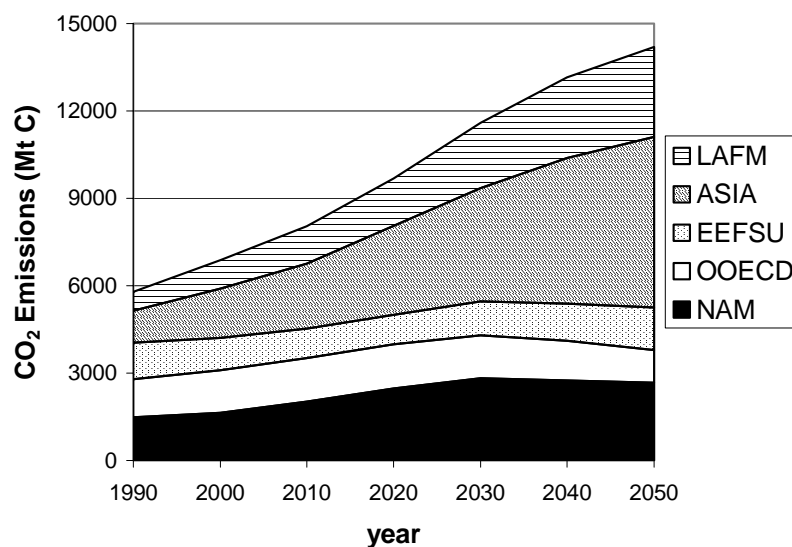


Figure 95. *Global regionalised CO₂ emissions. Reference scenario.*

8.2.1.2 Final energy

Figure 96 presents the evolution of the global final energy consumption and Figure 97 the corresponding market shares of the different fuels. In this scenario, a transition toward more flexible and clean, higher quality and grid-transported fuels takes place. Electricity, in particular, gains substantial share in the mix of final energy carriers. Oil products, on the other hand, decline their relative contribution but still maintain a sizeable portion of the final consumption, mainly due to the growth of the transportation demand and non-energy feedstocks. Natural gas also increases its share substantially. The fraction of consumption accounted for by solid energy carriers, such as coal and biomass⁸³, decreases substantially, while other fuels such as district heat, solar heat and hydrogen begin to penetrate the market.

⁸³ For simplicity, in the graph non-commercial and commercial uses of biomass are put together. The decline is mainly due to the prescribed decrease of the demand for non-commercial uses of biomass assumed in this scenario, as the different regions, particularly the developing ones, move towards commercial forms of energy.

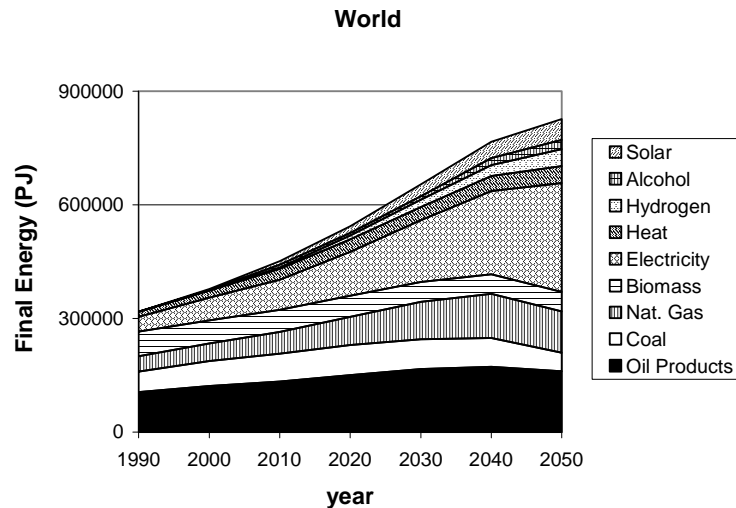


Figure 96. *Global final energy per energy carrier. Reference scenario.*

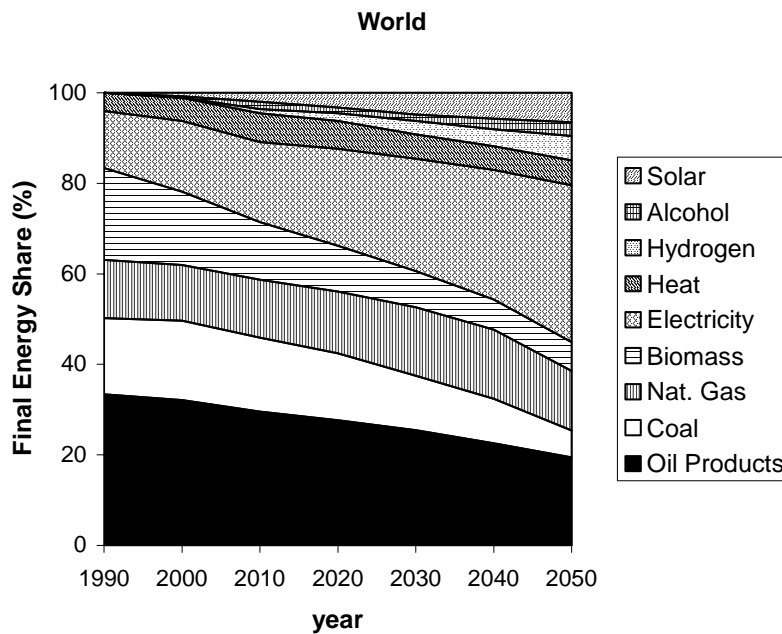


Figure 97. *Global market shares of final energy carriers. Reference scenario.*

8.2.1.3 Electricity generation

As already seen, in this scenario the importance of electricity in satisfying end-use demands raises continuously along the horizon in all regions. At the global level electricity generation experiences a vigorous growth at an average rate of 2.8% per annum for the period 1990-2050. The bulk of this growth is driven by the developing regions (ASIA and LAFM), which reach 57% of the total electricity generation in the year 2050 (see Figure 98). Clearly, a higher demand for electricity may drive to a faster rate of capital turn-over and could offer higher possibilities of learning for emerging generation technologies, although, of course, the specific learning potential depends also on other factors such as available natural resources.

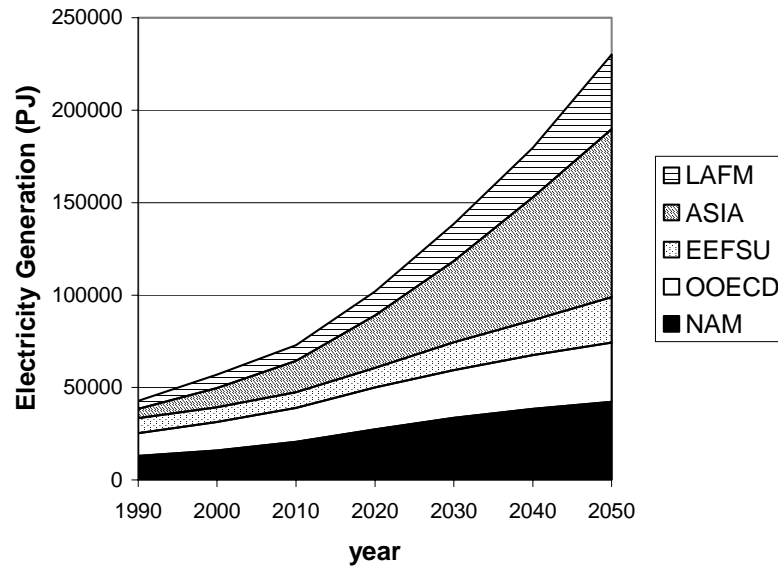


Figure 98. *Regionalised global electricity generation. Reference scenario. Global learning.*

The technology mix of the global electricity generation system is shown in Figure 99. Coal continues to be the most significant primary fuel for electricity production, but it is the clean coal technology that becomes predominant at the end of the time horizon. The gas combined cycle and the wind turbines experience a vigorous growth, while the gas fuel cell penetrates slowly. Cogeneration becomes an attractive option. Nuclear power essentially does not grow, but a substitution of conventional plants by new designs takes place. The amount of hydroelectric production grows only slightly. Solar photo-voltaics penetrates only very marginally, remaining in essence "locked-out".

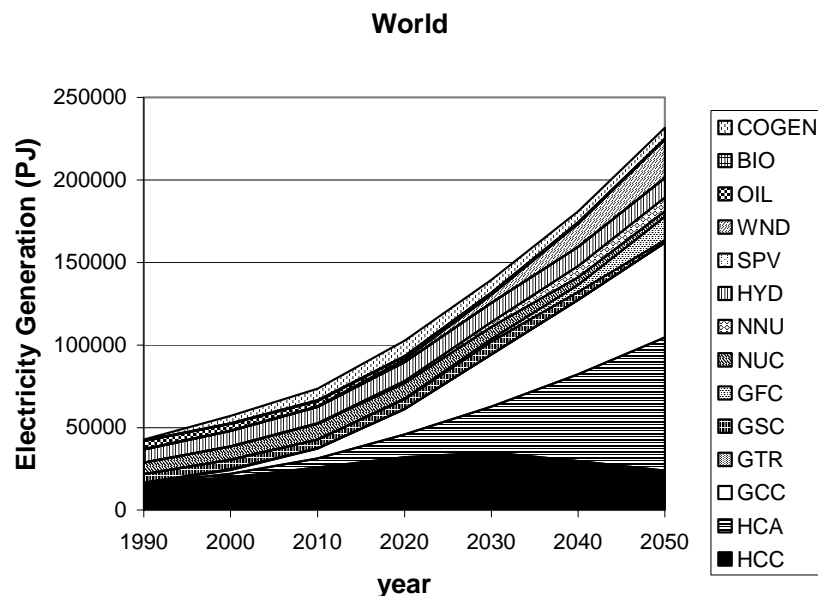


Figure 99. *Global electricity generation. Reference scenario. Global learning.*

8.2.2 Kyoto-trend scenario

The Kyoto-trend scenario, imposing a CO₂ constraint on the so-called Annex I regions, does not imply radical changes in the structure of the global energy system. Still, the system weans away from a carbon-intensive energy production. But, although industrialised and economies-in-transition regions reduce their emissions, global emissions continue to grow considerably driven by the dynamic growth of developing regions⁸⁴.

This case is used as an illustration of the gains of trade. No trade, Annex I-trade and full trade modalities have been considered here. For the full trade case two different possibilities have been taken into account. In the first one, developing regions join the trading system only in 2030. In the second one, global emission trading begins in 2010. The effects of their earlier incorporation to the permits market are shown.

8.2.2.1 Changes in the energy system

Figure 100 presents the comparison of primary energy consumption under the different scenarios. Emission reductions are achieved mainly by shifting away from coal. Natural gas maintains the predominance in primary energy consumption, experiencing a slight increase when no trade is possible and corresponding decreases when it is. Nuclear power, solar energy and commercial uses of (carbon-free) biomass augment their contribution and are the main responsible for the reduction of carbon emissions. In the full trade cases coal experiences some revival in the Annex I regions.

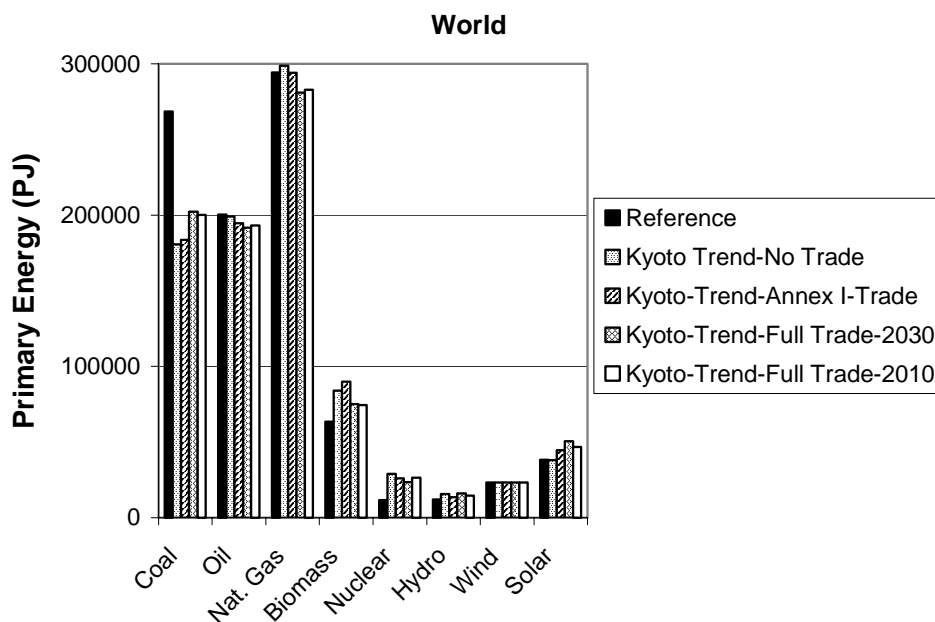


Figure 100. Global primary energy consumption in 2050. Reference and Kyoto-trend scenarios.

⁸⁴ Many studies have already pointed out the inefficiency of the Kyoto Protocol, or its extension in time, in achieving significant reductions of the global CO₂ emissions in the long-term. See, for instance, Nordhaus and Boyer (1999) for an interesting analysis and critique.

Figure 101 presents the global final energy consumption for the year 2050 in the different cases. Coal and natural gas decline their contribution at the final level in the constrained ones. Oil, heat and hydrogen increase their market share. Electricity fluctuates but still remains the energy carrier with highest market share.

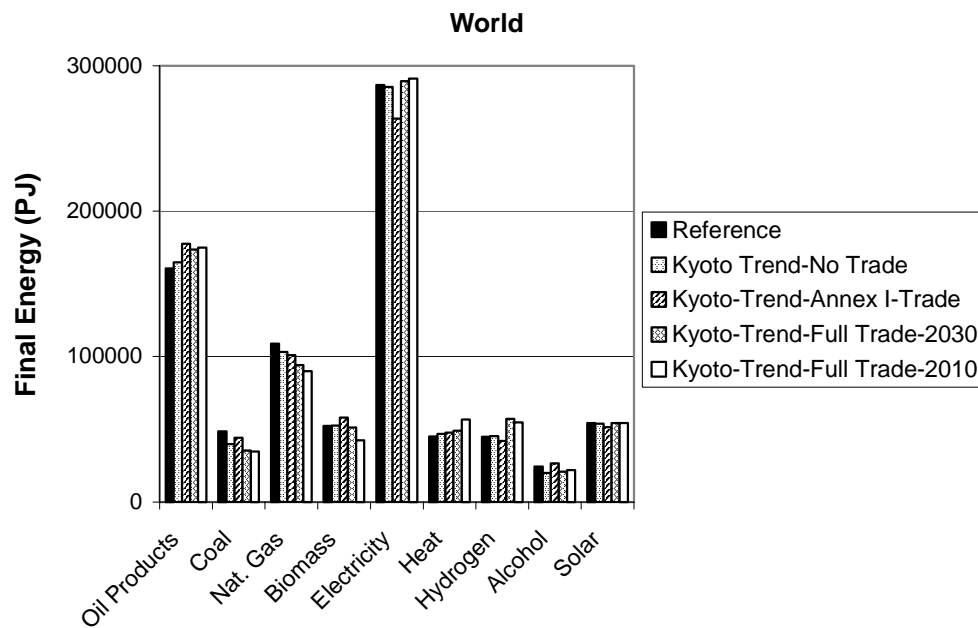


Figure 101. Global final energy consumption in 2050. Reference and Kyoto-trend scenarios.

In Figure 10, a comparison of the electricity generation mix in 2050 for the different variants of the Kyoto-trend scenario is shown.

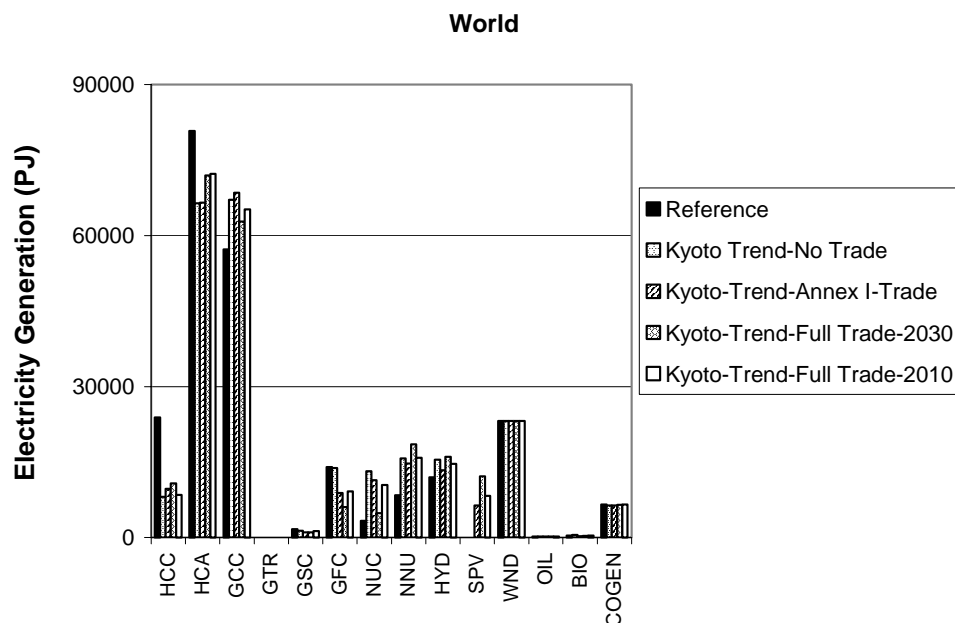


Figure 102. Global electricity generation in 2050. Reference and Kyoto-trend scenarios. Global learning.

The contribution of the electricity system to the emissions reduction is achieved mainly through fuel switching from coal to natural gas, the less carbon-intensive fossil fuel, and higher penetration of zero-carbon alternatives. Thus, coal plays a much more reduced role as primary fuel for electricity generation than in the baseline situation, particularly in the no-trade and Annex I-trade cases. Advanced coal technologies dominating the fraction of coal-fired generation remaining at the end of the horizon. The gas combined cycle, hydro and nuclear (both conventional and advanced) power plants increase their output. Wind turbines continue to grow at the maximum available rates, cogeneration continues to be an attractive option and solar PV begins to make a dent. The gas fuel cell, on the other hand, reduces its role in the cases where trade is permitted.

A noteworthy effect of emissions trading on the deployment of several low-carbon technologies (e.g. solar PV and new nuclear power plants) can be noticed there. Their global penetration in the Kyoto-trend scenario is higher for the cases where global trade is allowed. However, from the two cases with full trade, the growth was higher when full-trade was allowed later.

This provides an interesting insight into the response of the model when both learning and trade mechanisms are interacting within this perfect foresight framework. With a later full-trade (i.e. after 2030), it is still required to set in motion the learning processes of expensive low- or zero- carbon technologies in the regions with commitments. With global learning spillover, non-committed regions also benefit from such processes, and the early deployment of such technologies contributes to preparing them for a later participation in the trading system (as sellers). However, an earlier allowance of global trade makes cheaper mitigation options somewhere else available sooner, de-stimulating the deployment of promising, but expensive low-carbon options in constrained regions. Thus, this early full-trade can reduce the incentives to activate the learning mechanism in the constrained regions and, therefore, the corresponding spillover to non-constrained regions decreases. This may hinder the learning of those technologies and, consequently, they could reduce their global penetration in the long-term.

But, there is an additional effect that also plays a role. Incentives for early learning exist, but they are placed now in the regions that are likely to become permit sellers. With international spillover, those incentives may drive to the deployment of low-carbon technologies in unconstrained and constrained regions alike. Ultimately, the global penetration of such technologies will depend, other things equal, on the outcome of those two mutually offsetting factors. However, it is clear that even if large learning potential for expensive low-carbon technologies exists, if other options such as fuel switching from coal to natural gas are available in the selling regions, tapping such learning potential could be less attractive. The risk exists that if the signals given by the trading system are not correct, preference for cheaper options, which could lie within the current fossil-fuel technological regime, may hinder the transition towards a different, less fossil-intensive technological trajectory of the global energy system, necessary to achieve more profound emission cuts in the long-term. In reality, of course, the issue is much more complex and the outcome of those processes cannot be easily foreseen.

As an additional illustration, Figure 103 presents the evolution of the global electricity generation for the Kyoto-trend case with full trade since 2010.

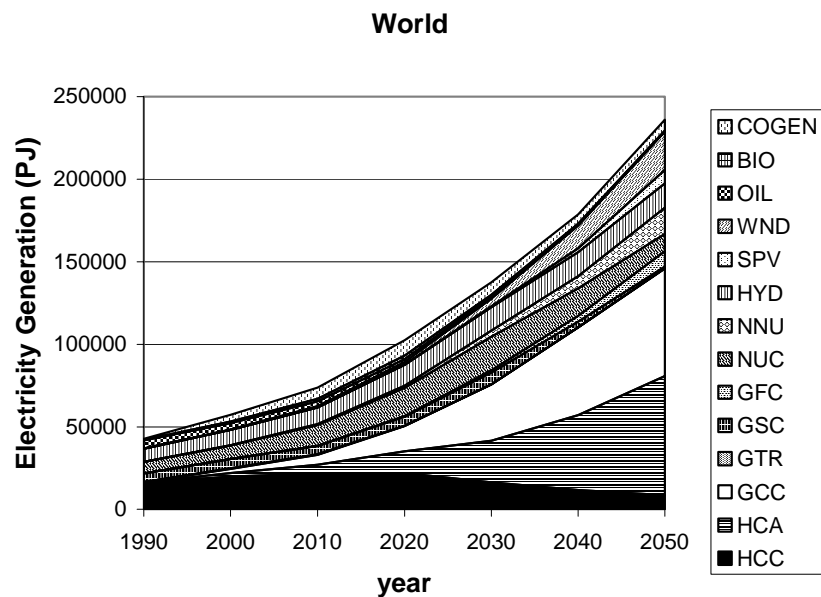


Figure 103. *Global electricity generation. Kyoto-trend scenario. Full trade from 2010.*

8.2.2.2 Emissions and mitigation costs

Figure 104 depicts the emissions in each region for the year 2050. At the global level the Kyoto-trend target entails a reduction of approximately 15% from the reference emissions. On a regional basis, however, it implies a substantial emissions cut for the NAM and EEFSU regions as compared to their baseline emissions. For the OECD it is much less significant because, as mentioned before, this region already exhibited a declining emissions trend in the baseline scenario. With Annex I trade, the NAM and OECD regions increase their emissions, as they buy permits from the EEFSU, which in its turn reduces further the level of emissions in order to sell. The allowance of full trade enables Annex I regions to emit more, as the developing ones assume part of their mitigation targets. In particular, NAM profits largely from such situation.

Again, it is important to notice here an interesting effect of the global learning spillover assumption. Developing regions do not face emission constraints (additional to their baseline caps) and in the Kyoto-trend scenario without trade or with Annex I-trade they do not have an incentive to reduce emissions. Nonetheless, in the Kyoto-trend-Annex I-trade case the emissions of ASIA are already below its baseline cap, due to, basically, fuel switching from coal-fired to gas combined-cycle production of electricity. Abatement efforts in the Annex I countries stimulate learning, rendering some less carbon-intensive technologies more cost-effective and therefore attractive also in other regions, driving to a positive effect in their emissions profile. Although the effect is not big here, among other reasons because the learning is concentrated only in electricity generation technologies, it is an indication of the positive effects of induced technology spillover (Grubb et al., 2000).

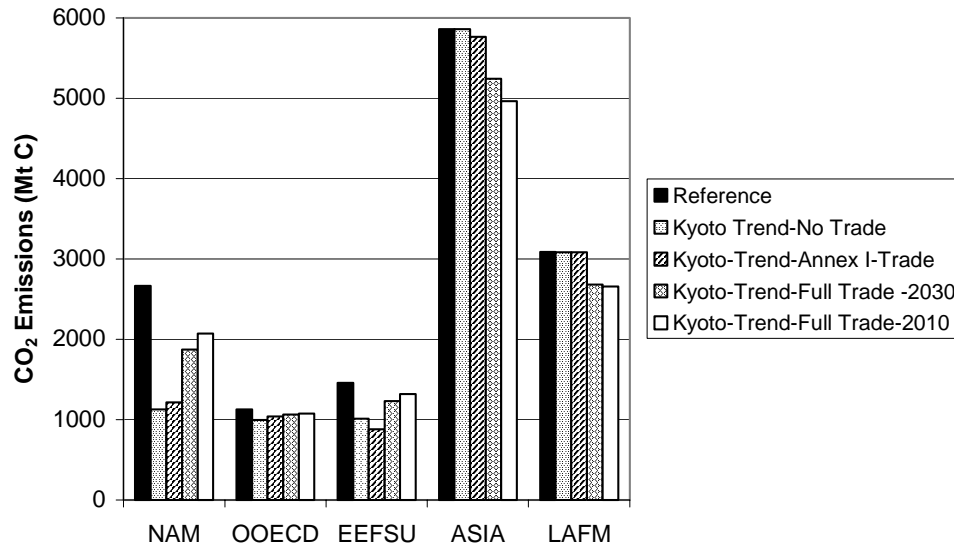


Figure 104. Comparison of CO₂ emissions per region in 2050. BaU and Kyoto-trend scenarios.

Figure 105 presents the total global discounted costs of CO₂ mitigation for the different variants of the Kyoto-trend scenario, computed as the difference between the total global discounted system costs in the baseline case and those of the constrained cases.

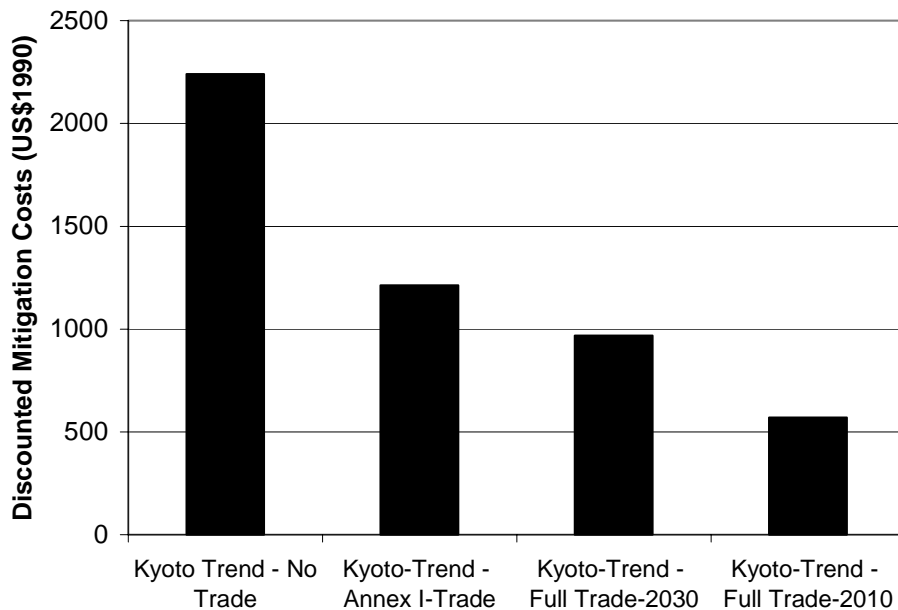


Figure 105. Total discounted global CO₂ mitigation costs. Kyoto-trend scenario. Different modalities of emissions trading.

There are significant disparities in the costs of implementation of the Kyoto-trend target in the different variants. If each Annex I region has to achieve its target on an isolated basis the abatement costs are high. The allowance of trade of emission permits, either between Annex I regions or at the global level, improves substantially the cost effectiveness of the abatement efforts. Also, an earlier incorporation of the developing regions (ASIA and LAFM) to the trading system contributes to lower the costs

significantly. The no-trade variant is almost five times more expensive than the full-trade-2010 one.

It is important to understand the burden sharing between the different regions. Also, an important issue concerns how the assumption of global learning may affect the system costs under the different cases. In this "bottom-up" framework the mitigation costs for a given region have two components. The first is the difference between the total discounted regional system costs in each of the Kyoto-trend cases and the corresponding baseline costs. This corresponds to the costs of the changes effected in each regional energy system in order to fulfil the emissions reduction target, i.e. the domestic mitigation costs. The second component is the money transferred due to sales/purchases of permits to/from other regions⁸⁵.

The domestic abatement costs are examined first. Figure 106 presents the difference between the total discounted system costs in each of the Kyoto-trend cases and the corresponding baseline costs for each region. The global difference (already examined above in Figure 105) is also shown for comparison.

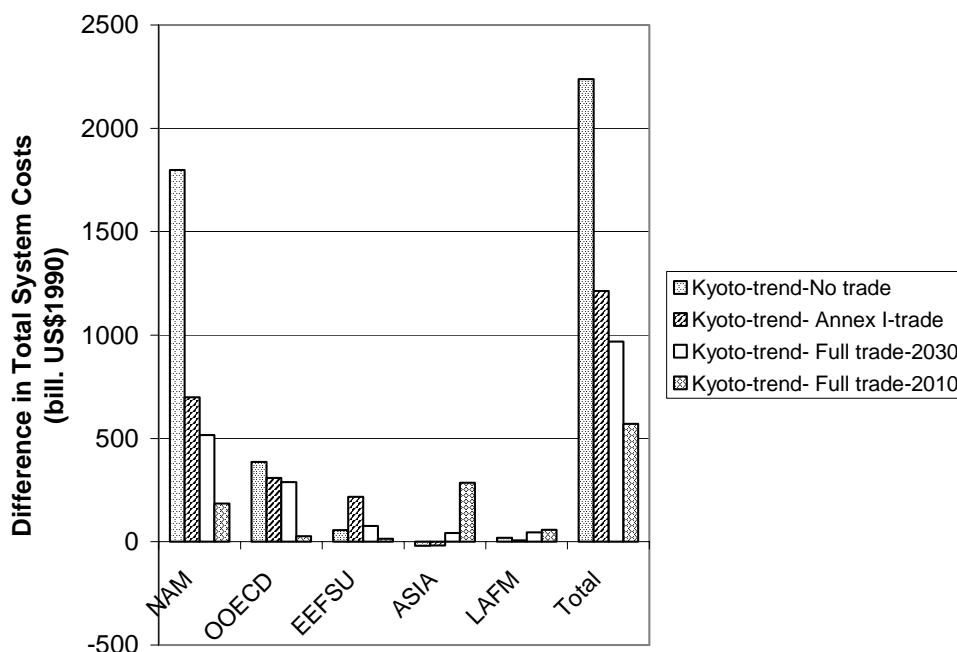


Figure 106. *Difference in the total discounted system costs from the baseline in each region. Kyoto-trend scenario. Positive values imply additional costs.*

If there is no trade the difference in system costs corresponds directly to the abatement costs. In this situation, Annex I regions have to achieve the target through in-house measures. Mitigation costs are high, especially for the NAM region. As for the burden share, NAM and the OECD bear, respectively, 78% and 20% of the total discounted global abatement costs.

⁸⁵ At the global level the difference between discounted system costs in the reference scenario and those in the constrained one correspond to the mitigation costs because the net transfers of money due to sales/purchases of emission permits across regions are zero. This is also the case at the regional level when no emissions trade is considered.

As expected, the system costs of constrained regions diminish appreciably when they are allowed to buy CO₂ permits. The decrease is particularly significant for the NAM region, although it still bears the bulk of the costs of domestic abatement efforts. In contrast, for selling regions the costs increase, as they undertake additional mitigation measures. Under the Annex I-trade situation, the energy system costs of the EEFSU region increase considerably. With full-trade, they are lower again but those of ASIA and LAFM rise.

But, there is an interesting detail here, which is due to the global learning spillover. In the no-trade and Annex-I-trade situations, where only the learning mechanism accounts for interactions between the Annex I and non-Annex I groups, the costs of the energy system in ASIA decrease, while those of LAFM increase (although the latter only very slightly). The reason is that, in order to curb emissions in the Annex I group, the system pursues the substitution of the gas combined-cycle for coal-fired power plants there, stimulating its cost reduction. Under full global learning spillover this renders the combined-cycle more attractive also in the ASIA region driving, as mentioned above, to change from conventional coal-fired to gas-fired generation there. This results in a decrease of the region's total discounted system costs. In the no-trade case lower emissions due to this effect are not observed because the model compensates emitting more somewhere else in the energy system. But, in the Annex I-trade case, the higher penetration of the combined-cycle drives to an effective reduction of emissions below the baseline, as mentioned before.

In the case of LAFM the interaction is somewhat more complex. As the gas combined-cycle is already penetrating at its maximum rate in the baseline scenario, no additional growth can be observed. But, an additional phenomenon is noticed. The de-stimulation of the learning process of the advanced coal power plant in Annex I regions, due to the need of reducing carbon emissions, also reduces the competitiveness of the technology in LAFM, driving to a slightly lower output. This is partially compensated by a slightly higher production of the conventional coal plant, but results also in an overall reduction of the electricity generation. In consequence, changes in the mix of final energy carriers are observed. Specifically, hydrogen and oil products are now favoured. Emissions are also slightly reduced below the baseline bound. As a final result the region's discounted system costs become higher.

Of course, in this analysis only the effects due to the interactions triggered by the learning mechanism in the electricity generation system can be observed. It would be very interesting to examine the outcome when learning is incorporated also in other energy chains. That would allow a more comprehensive assessment of the impact of learning in the estimation of the abatement costs.

Before examining the total regional mitigation costs, it is useful to discuss first the trade patterns, responsible for the money transfers across regions. Figure 107 presents the flows of permits across regions when Annex I-trade is allowed. In this situation the EEFSU block sells permits to the industrialised regions. NAM is the major buyer of CO₂ units. The OOECD buys, of course, much less in absolute amounts but increases the fraction of purchases along the horizon.

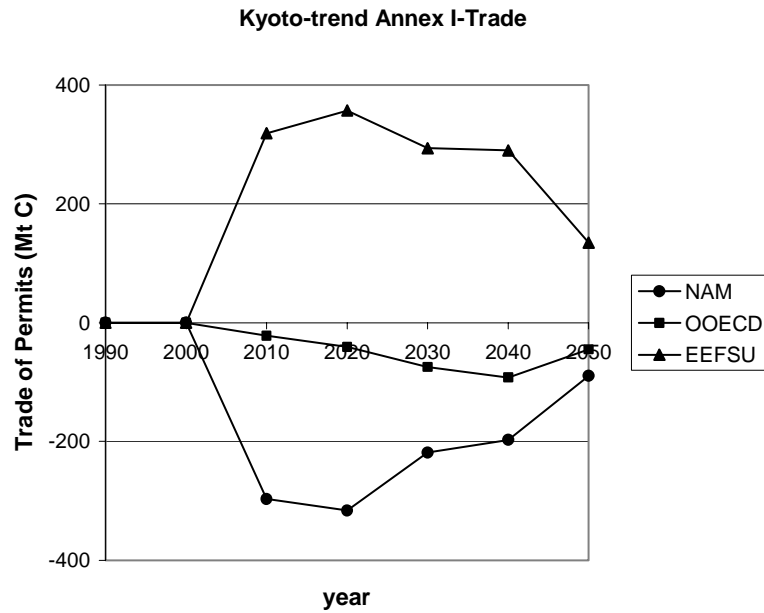


Figure 107. Trade of emission permits. Kyoto-trend scenario with Annex I-Trade. Positive values are sales and negative ones purchases.

Figure 108 depicts the transactions of CO₂ permits along the time horizon when non-Annex I regions join the market only in 2030. That is, trade is restricted to Annex I regions in the period 2010-2020 and is expanded to the global scale in the period 2030-2050. Under these circumstances, NAM and the OECD are the main buyers along the horizon. The EEFSU is still the main seller during the Annex I-trade stage, becoming a purchaser only in 2040. Once permits from the developing regions become available, the volume of transactions increases substantially. Initially, the LAFM takes the lead as main supplier of mitigation options but a rapidly growing amount flows from ASIA, which becomes the major seller at the end of the horizon.

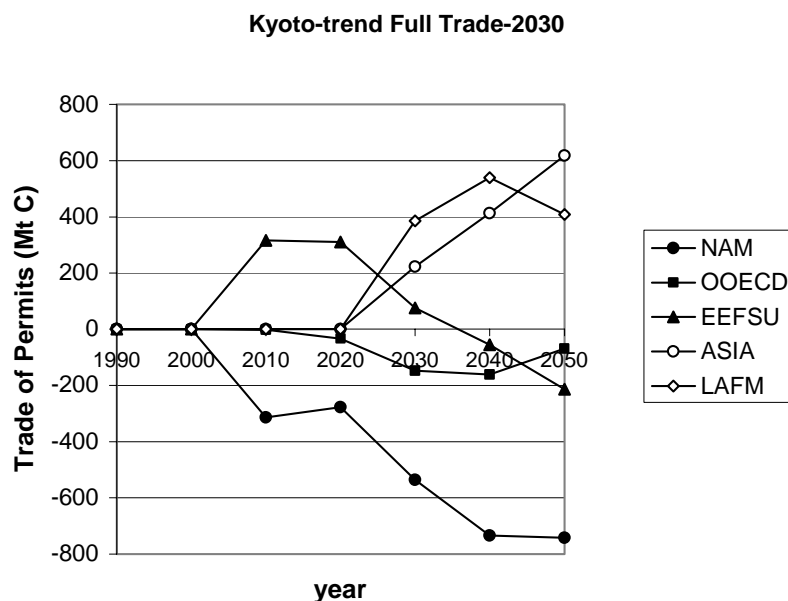


Figure 108. Trade of emission permits. Kyoto-trend scenario with full trade after 2030. Positive values are sales and negative ones purchases.

Figure 109 shows the emissions permits exchanged between the different regions in the full-trade-2010 variant. Here, all regions are trading partners from the outset in 2010. The total amount of transacted permits increases substantially in this situation. NAM is by far the main permit purchaser. The OOECD region is also an important buyer of permits but the purchased quantities decrease after 2030, as their energy needs and associated emissions decline. The EEFSU is a permits seller during the first periods but, afterwards, as its economy recovers and energy needs begin to grow substantially again, it becomes a purchaser of CO₂ permits. In the developing world, ASIA constitutes the main seller of permits followed by the LAFM region.

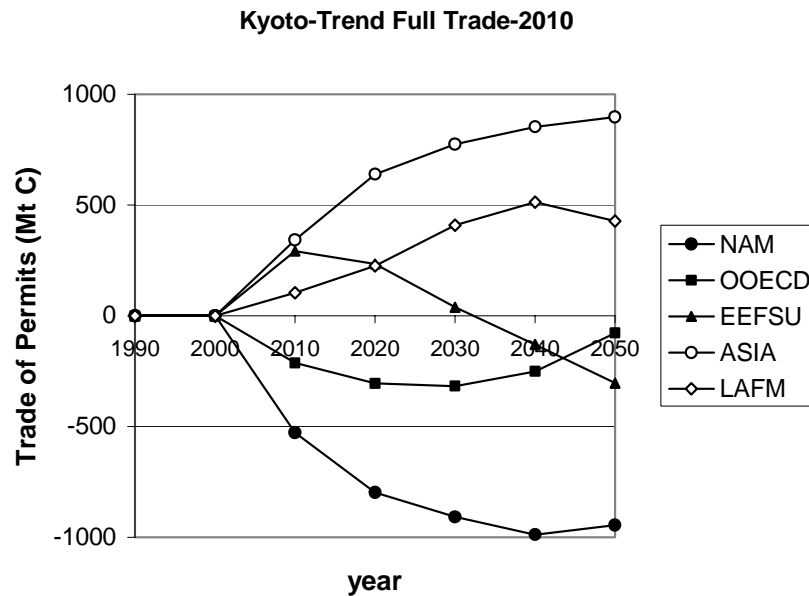


Figure 109. Trade of emission permits per region. Kyoto-trend scenario with full trade from 2010. Positive values are sales and negative ones purchases.

The trade flows presented above imply large transfers of money across regions⁸⁶. Figure 110 presents the total discounted value of money transfers made (received) by the different regions due to permit purchases (sales). Payments of permits have been valued at the marginal costs of CO₂ provided by the model. Transfers take place from NAM and OOECD to the EEFSU and the developing regions. The bulk of the resources flows from the NAM region, the main permits purchaser. With Annex I-trade, net payments go completely to the EEFSU. With full-trade after 2030, EEFSU still receives most of the money but the other regions receive also sizeable amounts. If the full trade takes place from 2010, ASIA becomes the main recipient of transfers, followed by LAFM and EEFSU.

⁸⁶ Some authors (e.g. Victor et al., 1998) have suggested that such transfers could be redirected to support the development and deployment of low-carbon technologies and associated infrastructures in the receiving regions in order to contribute to "lock-in" the decarbonisation process of their energy systems.

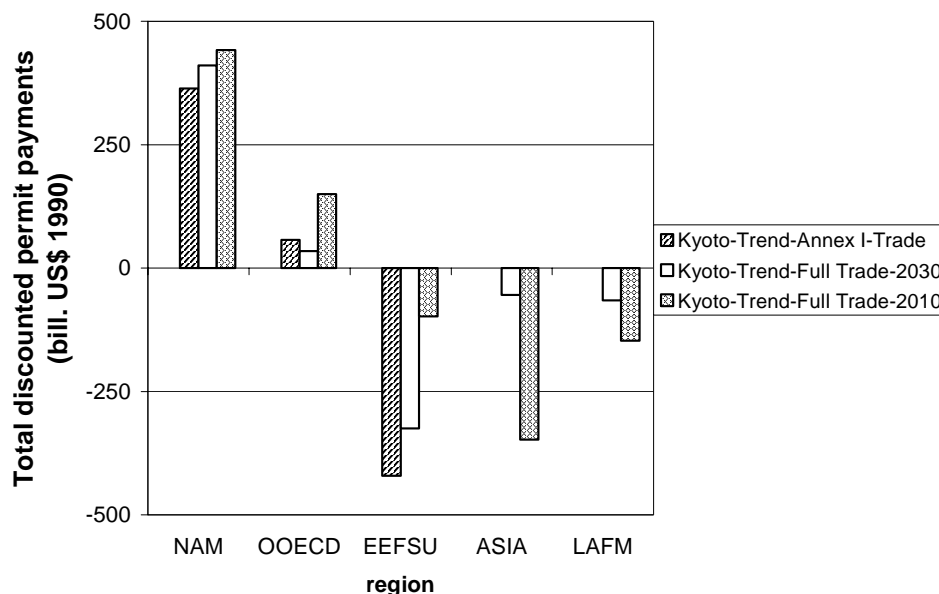


Figure 110. Total discounted money transfers due to sales/purchases of CO_2 permits. Positive values are expenditures and negative values revenues.

Finally, the total discounted mitigation costs per region, adding both the costs of domestic abatement and the permit payments/revenues, are shown in the Figure 111. Under the trading cases, net costs are borne by NAM and OECD and net benefits taken by the EEFSU, ASIA and LAFM regions. But, even with the large transfers of money made by the industrialised regions towards the EEFSU and the developing regions, they are still better off under the trading regimes.

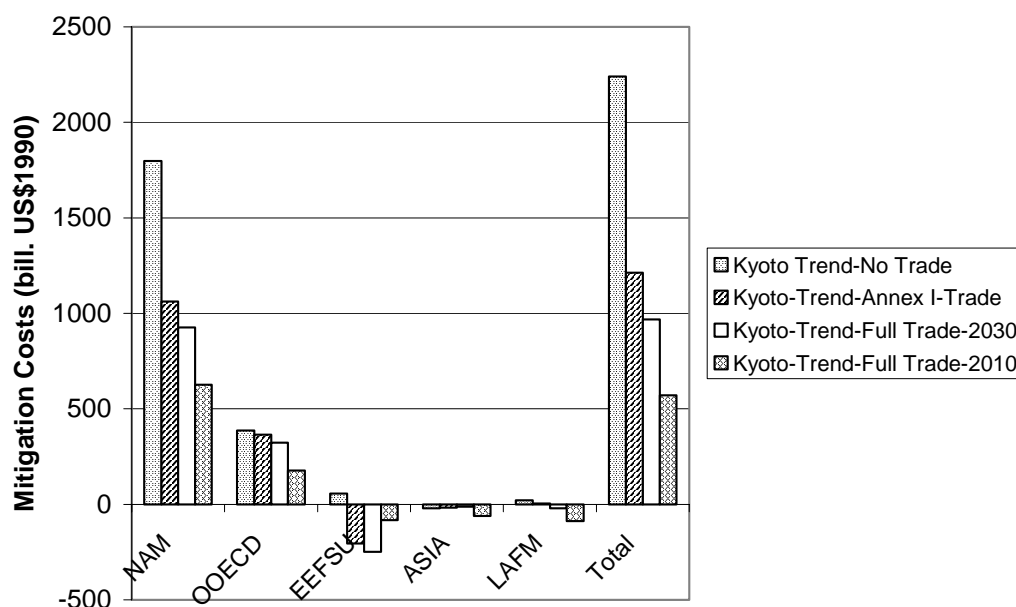


Figure 111. Total discounted CO_2 mitigation costs per region. Kyoto trend scenario. Different modalities of emissions trading. Positive values are costs and negative ones benefits.

8.2.2.3 Deployment of learning technologies

Figure 112 presents the output of the different learning electricity generation technologies in each region for the year 2050 under the baseline conditions and the different variants of the Kyoto-trend scenario.

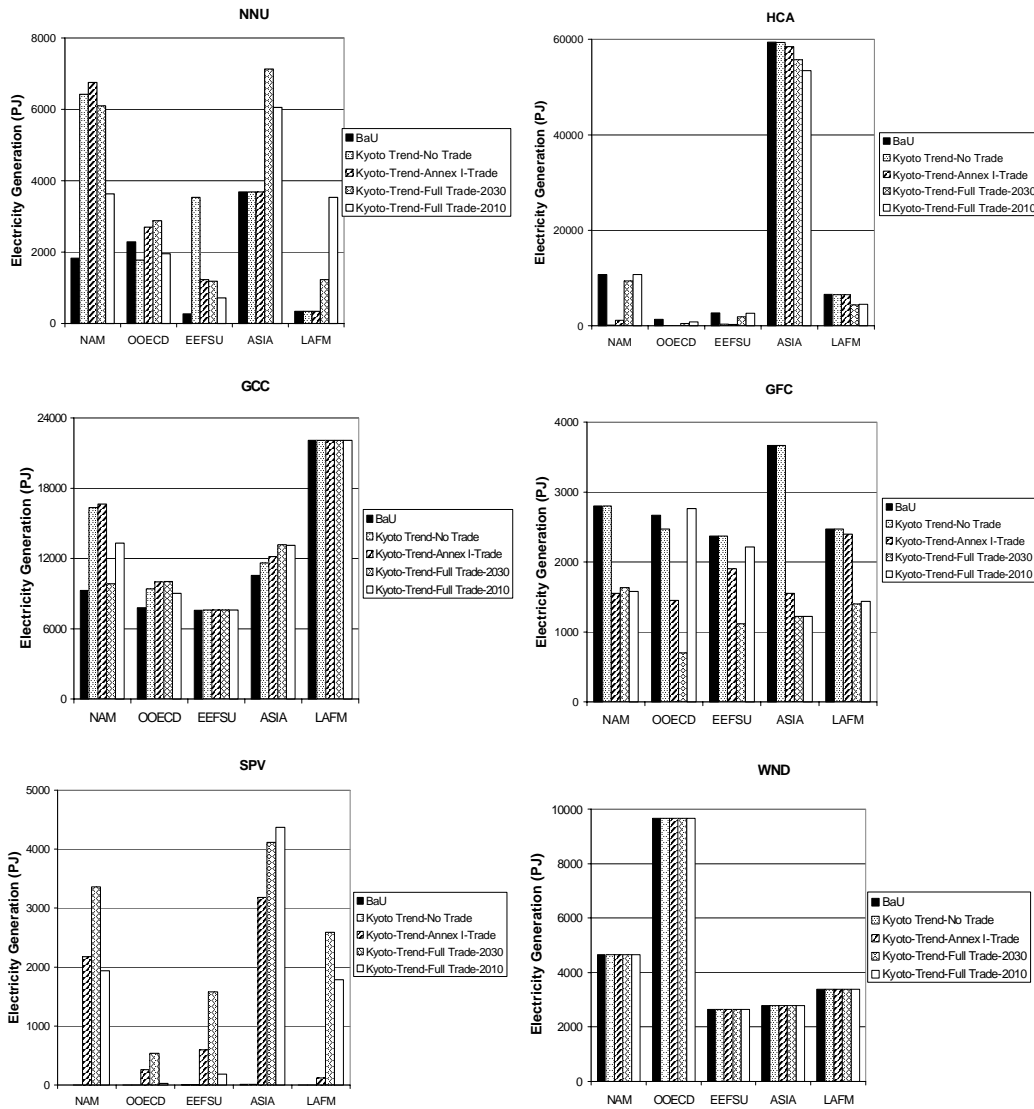


Figure 112. Output of learning electricity generation technologies in 2050. Reference and Kyoto-trend scenarios.

The penetration of the different technologies depends on numerous factors such as the particular conditions of the regional energy systems, the maximum availability of natural resources, the size of the demand for electricity, the maximum rates of penetration, the learning rates and the scale of the learning process, the presence and magnitude of a CO₂ constraint, the modality of emissions trading as well as the volume of permits sold/bought by each region, among others. Therefore, singling out the influence of the different factors is a difficult task. However, one can still try to provide an interpretation of the main mechanisms involved.

The advanced coal technology experiences a significant deployment, particularly in the ASIA and NAM regions. Its diffusion across regions is, of course, affected by the presence of the Kyoto-trend constraint as follows. In the regions facing carbon constraints, its penetration is largely diminished if no trade or only Annex I-trade is possible and increases again when full trade is allowed. In the developing regions the contrary occurs. There, the technology penetrates less under the global-trade umbrella as their energy systems shift away from coal in order to sell permits. Therefore, a later allowance of global trade produces lower installations in Annex I regions and higher in the non-Annex I group. At the global level, the cases with full trade show a higher output than no- or Annex I only- trade ones.

The new nuclear power plant penetrates to some extent in the reference scenario, particularly in ASIA, the OOECD and NAM regions. With the imposition of the Kyoto-trend target its role becomes more significant. Without trade the technology boosts, growing substantially above the baseline levels in NAM and also in the EEFSU, the latter a region where its growth under baseline conditions was not significant. Both conventional and new nuclear power plants increase their output in EEFSU, but advanced nuclear takes the lead. On the other hand, output is somewhat reduced in the OOECD region, where conventional nuclear output augments. Its share in the EEFSU electricity mix diminishes again under the Annex I-trade case, as it recedes in the competition with conventional nuclear, but increases in NAM and OOECD. With full trade after 2030 the technology still results attractive in Annex I regions, although its output is slightly reduced in NAM. Also, it increases its growth in the non-Annex I regions, which have an incentive to deploy due to the presence of the trade linkage. Specifically, the technology reaches its highest growth in ASIA.

Under the global-trade-2010 case two counterbalancing effects play a role in the diffusion of the technology, namely the disincentive to deploy in Annex I regions, which now can buy permits earlier, and the incentive to do so in non-Annex I ones that may sell them. As a consequence of the first factor much less capacity is built in the Annex I group, which now acquires cheaper permits from the developing world. As for the developing world, an increase takes place in the LAFM region, which now sells a higher absolute volume of permits. But, due to the global learning spillover assumption, the effects of the weaker stimulus in the Annex I group are felt in the whole system. Less capacity is built in ASIA in this case than in the full-trade-2030 situation.

The gas combined-cycle constitutes an attractive option in all regions⁸⁷. In EEFSU and LAFM it penetrates along the maximum growth rate both in the baseline scenario and all the variants of the Kyoto-trend one. In the industrialised regions the imposition of the Kyoto-trend constraint without trade or with Annex I-trade stimulates its growth, as

⁸⁷ Some authors (Wene, 2000) have suggested that shifting from coal plants towards the currently highly competitive combined-cycle gas turbines, although favourable for the mid-term CO₂ emissions reductions, being natural gas the less-carbon intensive fossil fuel, entails the risk of "locking" the system into such technology, obstructing the penetration of more radical technological innovations that could contribute to a further decarbonisation of the generation mix in the long-run. Others, however, see in the gas combined-cycle one of the pillars of a possible transition towards a "methane age", which, in its turn, should be the bridge to carbon-free energy systems in the very long-term (Nakicenovic, 2000).

it replaces coal-fired generation. When non-Annex I regions join the trade, its output is reduced in NAM but increases in ASIA. As for the effects of an earlier global trade, they are different in the NAM and OOECD regions. With full trade beginning in 2010, the capacity build-up is higher in NAM but lower in OOECD, as compared to the full-trade-2030 case. In the OOECD region the gas fuel cell is able to increase its output instead.

As for the gas fuel cell, under the particular conditions assumed here it results more attractive in the reference scenario than under the constrained one, as in the latter one the system appears to favour less intensive carbon options and the technology faces competition from the gas combined cycle and the solar PV, among others⁸⁸. However, in the Kyoto-trend-no-trade case it still results almost as attractive as in the baseline. But, with the introduction of trade, its role in the generation mix decreases. With Annex I-trade, a significant decrease takes place in the NAM and OOECD regions, and a lower, but still noticeable, decline in the EEFSU one. As a result, its penetration in ASIA is substantially affected, although its output in LAFM remains almost unchanged (due, among other factors, to the fact that in this case solar PV does not penetrate in this region, see below). Its penetration in all regions is lowest in the full-trade-2030 case. But, with an earlier allowance of global trade (in 2010) its growth recovers somewhat, lead by installations in the OOECD and EEFSU regions.

Solar photo-voltaics does not diffuse in the reference or Kyoto-trend-no-trade cases. Despite some investments taking place in the first periods, particularly in the OOECD region, the technology remains "locked-out". It is introduced, however, when either Annex I- or full-trade takes place. With Annex I-trade, introduction occurs mainly in NAM and ASIA, and to less extent in EEFSU and OOECD. In LAFM the technology remains marginal, but still some deployment takes place. Being EEFSU the main permit seller, an incentive for deployment exists there. However, the potential in the region is relatively small. Nonetheless, early investments there trigger the learning mechanism and penetration occurs also in the permit buying regions NAM (where the highest potential within the Annex I group is at hand) and OOECD, on the one hand, and non-

⁸⁸ This should not be interpreted as if the fuel cell did not constitute an attractive option in a CO₂-constrained world. The technology is, in fact very promising, and possesses a significant potential both in stationary and mobile applications in several sectors. More importantly, this is an example of how assumptions about relevant parameters and the treatment of technological change may affect the results of a model. In this regard, one aspect must be mentioned here, which, although applicable to all learning technologies, appears to particularly affect the fuel cell in this context. It is the fact that learning can take place not only in investment costs but also in fixed and/or variable O&M costs. If learning were allowed also in variable O&M costs the technology could enjoy some additional advantage. An additional point has to do with an important aspect that is not addressed here, namely technological clusters. Learning spillovers may manifest between related or similar technologies. As fuel cells may have applications on several areas, the possibility exists for clustering effects to be important. They may appear, for instance, between different alternatives for centralised and/or decentralised stationary electricity generation (e.g. natural gas, coal or hydrogen fuel cells) or between stationary and mobile applications (Gritsevkiy and Nakicenovic, 2000). This could also have an impact in the attractiveness of a given technology. This issue of the clustering effects drives us to a more general issue concerning the palette of technologies chosen as candidates by the analyst. That is, if, as in this case, only the gas fuel cell is considered, it could happen that the technology does not result particularly attractive. But, if the technology has the opportunity of learning together with others, the increased learning potential may render them attractive. Thus, in a model with learning clusters the choice of candidate technologies and their interrelations could have different consequences than in a normal linear programming model with exogenous costs trends or in the learning model used here, which excludes clusters.

constrained regions, (mainly ASIA where the highest potential exists), on the other hand. As no trade linkage exists between Annex I and non-Annex I groups, the penetration in the latter ones appears to be a result of learning spillover.

When full trade is possible, incentives for deployment are present mainly in the developing regions, the main permit providers. However, it is interesting to observe the effect of an earlier/later entrance of those trading partners. If they join the trade later (2030), this, on the one hand, leaves room for stimulating solar PV's learning in Annex I regions, since only a reduced trade takes place in the first periods after the constraint is imposed and domestic mitigation must still be carried out. On the other hand, there is an incentive to deploy the technology in non-Annex I regions because of the possibility of becoming permit sellers later. With the combination of these factors, solar PV reaches a higher level of diffusion in all Annex I regions, as compared to the Annex I-trade situation. Also, penetration is more aggressive in non-Annex I regions. In particular, PV installations rise much faster in the LAFM region.

Now, when the global trade takes place earlier (from 2010), there is much less incentives to bring it about in the Annex I regions and installations there are reduced (compared to both Annex I-trade and full-trade-2030 cases). However, the trade linkage encourages build-up of solar PV capacity in developing regions. This is particularly so in ASIA, which has both the highest potential and is the main permits supplier under these conditions, but it also occurs, although to a lower extent, in LAFM. The spillover, which occurs now in "the other direction", still results in installations in the Annex I regions, although mainly in NAM.

The wind turbine results very attractive under all conditions, expanding along its maximum growth constraint in all regions. The technology is already competitive at the starting point of its learning curve and further learning renders it more attractive⁸⁹. Specifically, the largest capacity build-up has effect in OOECD where the highest potential has been assumed here.

8.2.3 Kyoto-global trend scenario

The Kyoto global trend scenario imposes a much more stringent constraint on the emissions of the global energy system, as it involves targets for the developing regions after the year 2030. Two trading modalities have been considered: No trade and full trade, the latter with two sub-variants, namely with non-Annex I regions either joining the permits market in 2030 or taking part in it from the outset in 2010. Such scenario is presented as a complement to the Kyoto-trend one scrutinised above. However, only some illustrative results are presented and a much shorter discussion is made.

⁸⁹ However, it must be noticed that in the model it was not taken into account the fact that the costs of wind facilities are also influenced by the specific characteristics of their location. As the more attractive sites are occupied, rising costs may arise when moving towards less windy sites (Neij, 1999a, Petersik, 1999).

8.2.3.1 Primary energy

The imposition of constraints in all regions drives to substantial structural changes in the energy system. Coal, the most carbon-intensive fossil fuel, reduces drastically its participation in the primary energy supply, while gas, nuclear and the renewable resources increase it substantially. By the end of the horizon natural gas is the dominant primary energy source and non-fossil sources increase their participation. Nuclear, solar, sustainable uses of biomass and hydropower gain share. Also, the energy system becomes more efficient. In the year 2050, total primary energy consumption is reduced by about 12% compared to the baseline situation and the fraction of non-fossil resources increases from 16% to about 32%. Figure 113 shows the evolution of primary energy in the Kyoto-global trend case with full trade after 2010. Figure 114 presents a comparison of the primary energy mix between the different cases in 2050. For reference purposes the composition in 1990 as well as that in the reference and Kyoto-trend-full-trade-2030 cases in 2050 are also depicted.

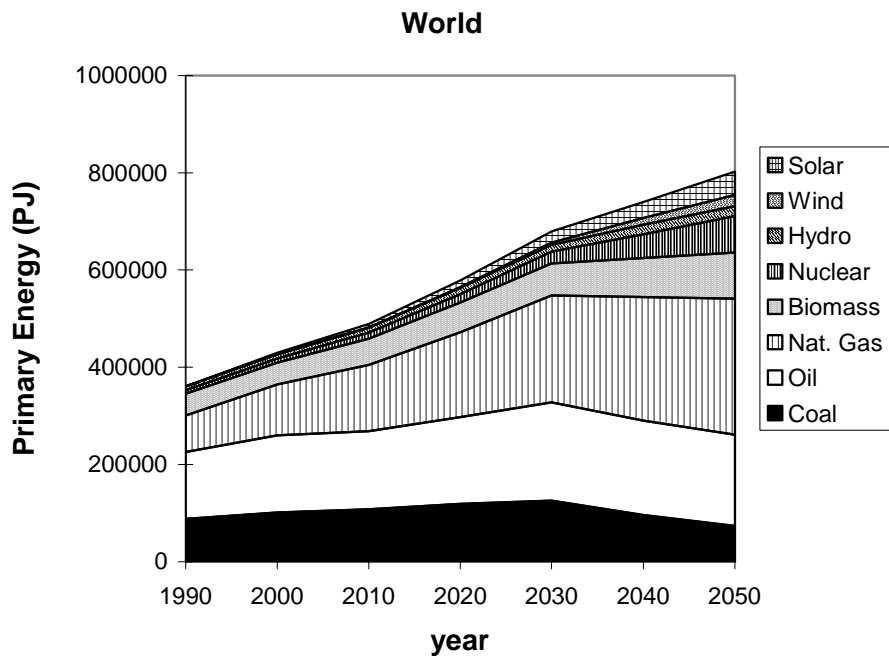


Figure 113. Primary energy consumption. Kyoto-global-trend scenario. Full trade from 2010.

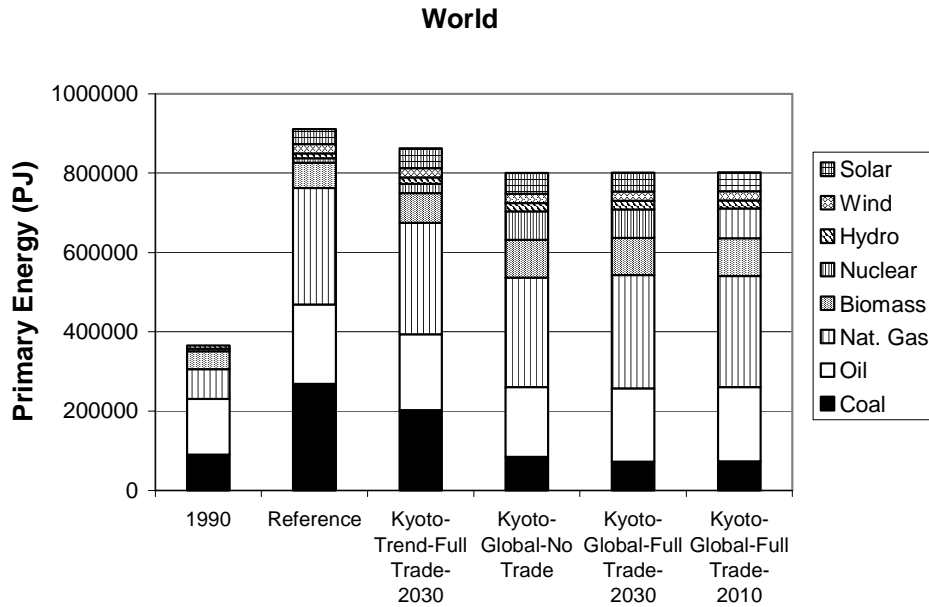


Figure 114. Global primary energy mix in 2050. Kyoto-global-trend scenario.

The evolution of the corresponding CO₂ emissions is shown in Figure 115. For comparison the global baseline and Kyoto-trend-full-trade-2010 emissions trends are also depicted. Following the strong Kyoto global-trend target, emissions peak in 2030 and begin to decline afterwards. Still, in the year 2050 the energy system emits around 8.6 Gt Carbon, which is approximately 50% above the level of global emissions in the year 1990.

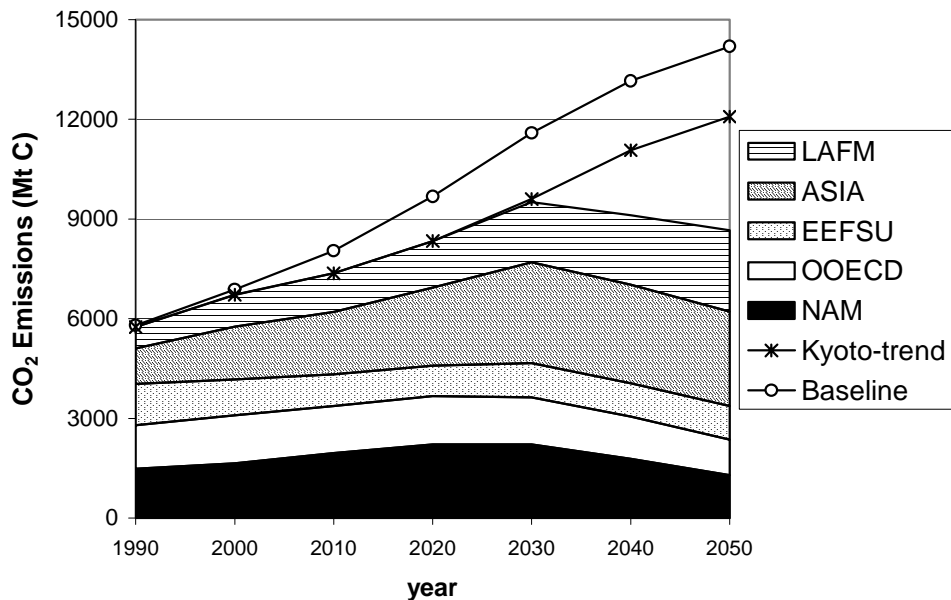


Figure 115. Global regionalised CO₂ emissions. Kyoto-global-trend scenario. Full trade from 2010.

Figure 116 presents the total discounted mitigation costs for this scenario. The economic benefits of allowing global trade and of doing so at an early stage can be appreciated also in this scenario.

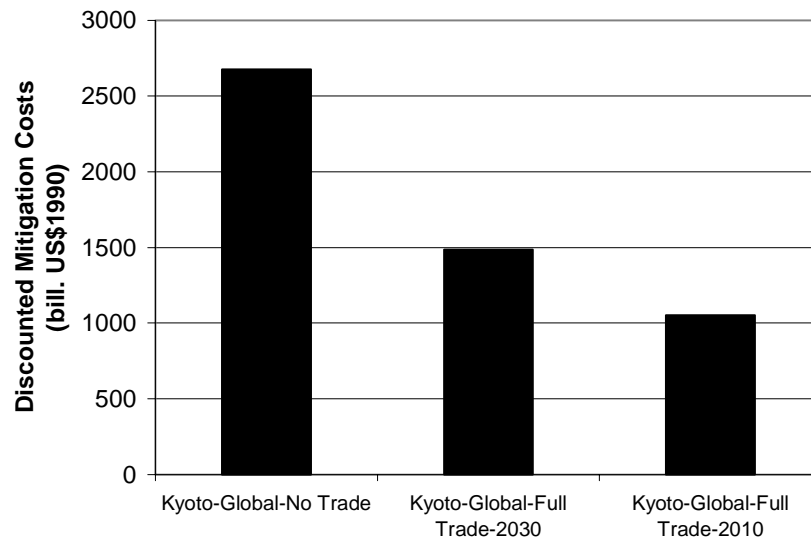


Figure 116. Total discounted global CO₂ mitigation costs. Kyoto global-trend scenario.

8.2.3.2 Final energy

Figure 117 shows the relative share of the different final energy carriers at the global level under the Kyoto global trend scenario. At the end of the horizon hydrogen, alcohol and heat have increased their participation as compared to the baseline case while coal and biomass have reduced it. Natural gas also experiences some reduction.

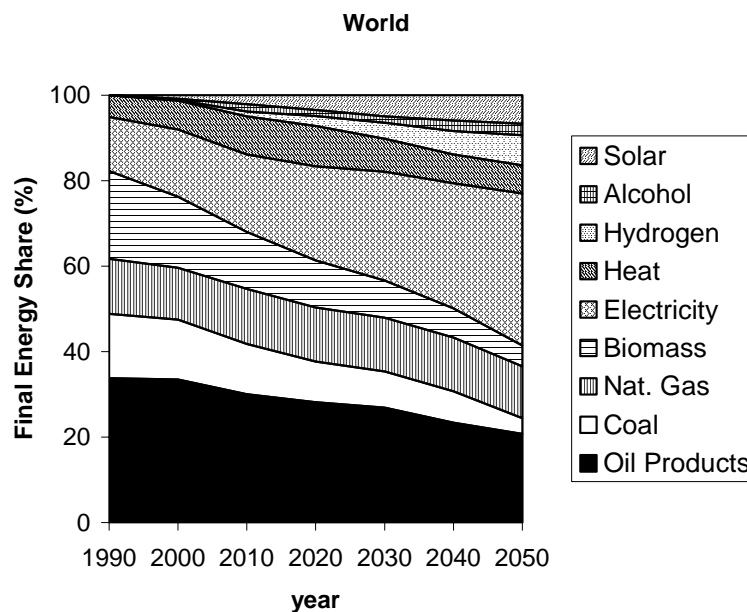


Figure 117. Global final energy share. Kyoto-global trend scenario. Full trade from 2010.

8.2.3.3 Electricity generation

Figure 118 shows the electricity generation per region in the different Kyoto global-trend cases. The regional composition in the year 1990 and that obtained in the reference scenario for the year 2050 are also shown here for comparison. In these scenarios electricity increases more than five times between 1990 and 2050.

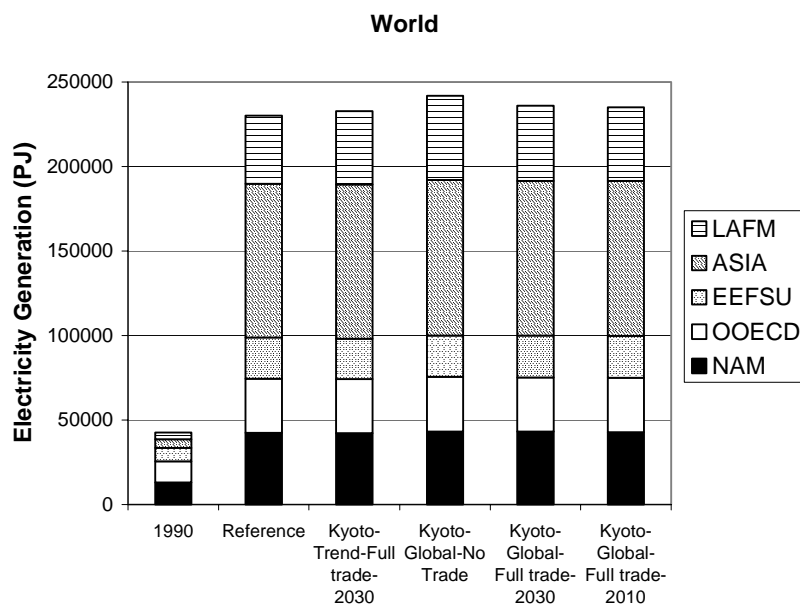


Figure 118. Global regionalised electricity generation in 2050. Kyoto-global-trend scenario. Global learning.

Figure 119 presents the comparison of the generation mix at the global level for the year 2050 in the different cases. As expected, under the more severe constraint coal-fired generation, from both conventional and advanced plants, is strongly reduced. In contrast, natural gas combined-cycle, solar PV, hydro and especially nuclear (conventional and advanced) power plants increase their production substantially.

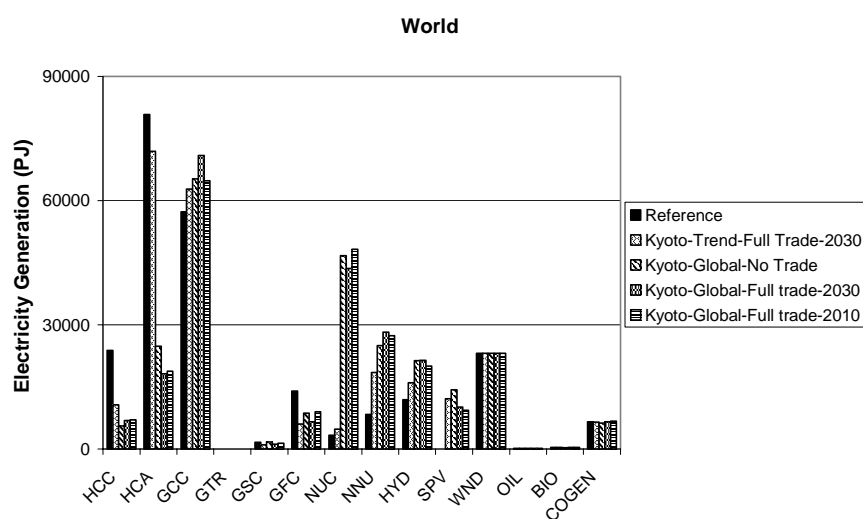


Figure 119. Global electricity generation mix in 2050. Reference and Kyoto-global trend scenarios. Global learning.

Figure 120 presents the evolution of the global electricity generation along the time horizon under the Kyoto-global-trend with full-trade-2010 case. Clearly, nuclear energy, with both conventional and new designs, plays the most important role in the contribution of the electricity system to the overall reduction of emissions. The gas combined cycle turbine also increases its global output and solar PV penetrates.

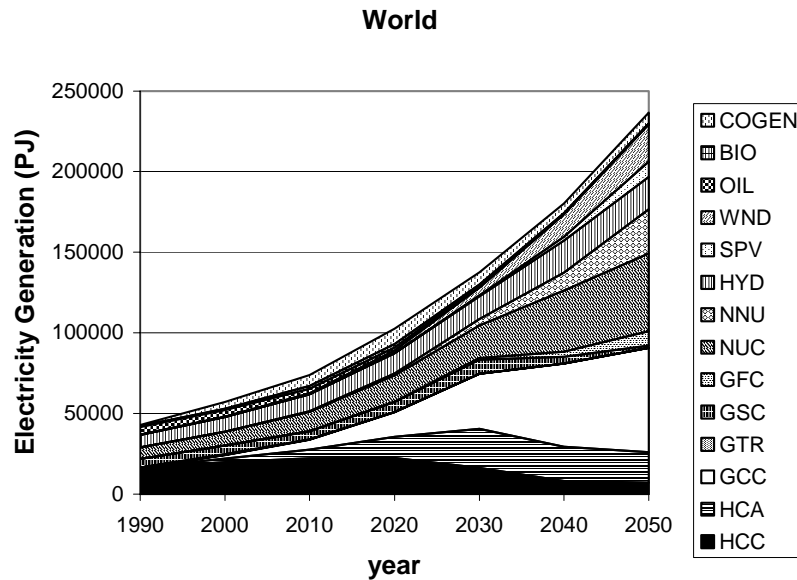


Figure 120. *Global electricity generation. Kyoto-global-trend. Full trade from 2010. Global learning.*

The levels of electricity production reached by the learning technologies in the year 2050 under the different variants of this scenario are shown in Figure 121. For comparison both the reference values and those obtained in the Kyoto-trend-full-trade-2030 case are also portrayed there.

The production of new nuclear power plants increases considerably in all regions, but especially in NAM, ASIA and LAFM. In NAM the technology is more vigorously introduced in the full-trade cases. The reason is that, under the full-trade umbrella, at the very end of the horizon the LAFM region becomes an important purchaser of permits⁹⁰, which come mostly from ASIA. This forces other regions, particularly NAM, to undertake more domestic reductions and triggers a more active penetration of this technology. In the OECD the growth in the full-trade-2030 case occurs at expenses of the conventional nuclear plant.

The advanced coal plant, on the contrary, reduces to a great extent its participation in the electricity production. The imposition of constraints also in developing regions destimulates its deployment all over the world. Specifically, without the possibility of trading permits, the technology practically disappears from the Annex I regions. With

⁹⁰ This region does not possess significant reserves of coal, as it does of oil and natural gas. Thus, already in the reference scenario it follows a natural gas intensive path, and the use of coal as primary resource remains low. Therefore, its potential to curb emissions by shifting away from coal is more reduced than in, for instance, ASIA.

trade, it is further reduced in ASIA but rebounds, although minimally, in the rest of the world.

The gas combined-cycle augments its output in NAM, OECD and ASIA in this scenario. In the industrialised regions (NAM and OECD), it reaches its highest penetration when full trade is allowed after 2030. However, if full trade is allowed from 2010, its growth diminishes slightly as the regions buy permits, allowing coal-fired generation to recover. Also, under the full-trade-2010 situation, the technology's built-up decreases in ASIA, as the region shifts towards less carbon intensive sources in order to sell permits. Both conventional nuclear and solar PV replace the gap left by the reduced expansion of the combined cycle turbine there.

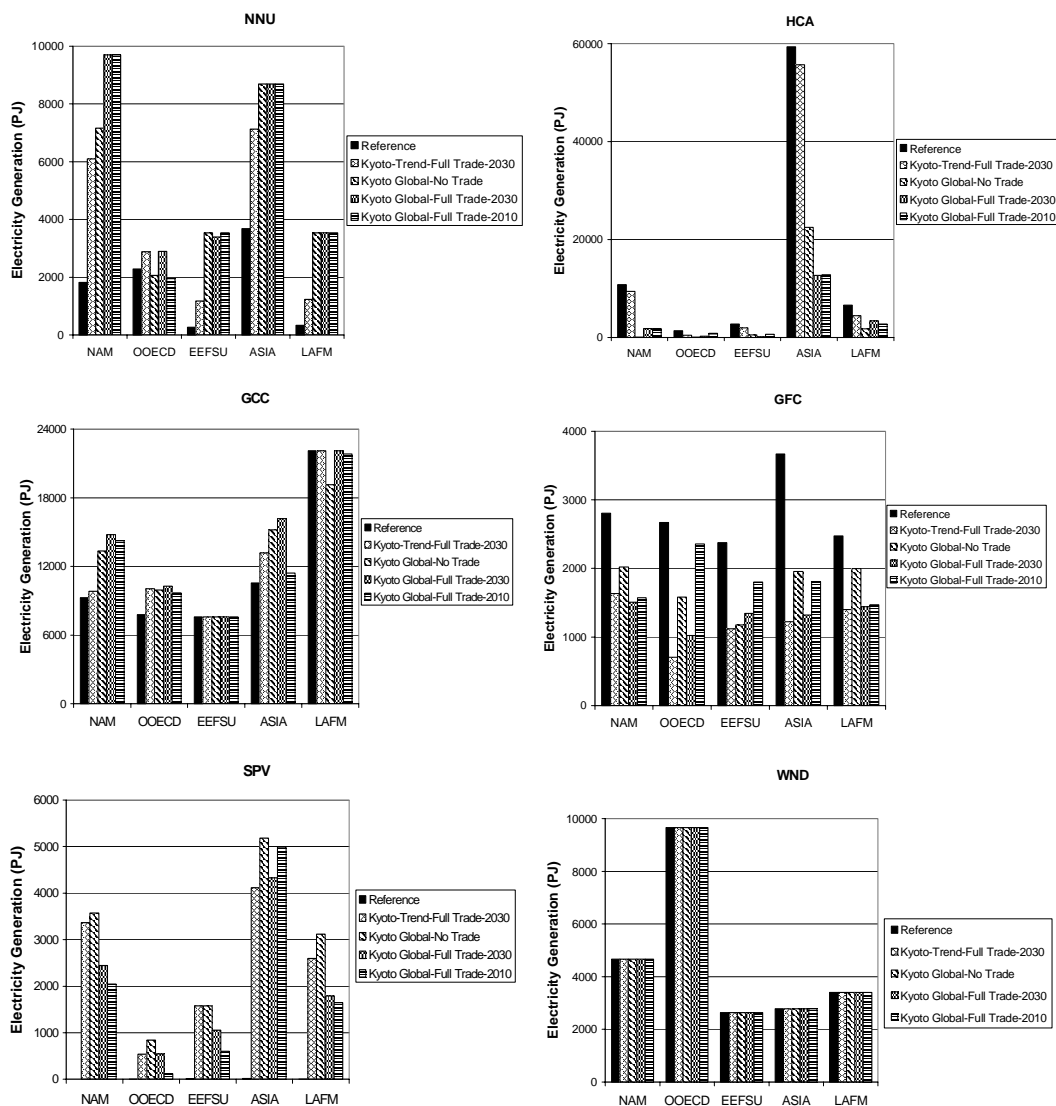


Figure 121. Electricity generation of learning technologies in 2050. Kyoto global-trend scenario. Global learning.

In LAFM, the technology grows almost as much as under baseline conditions when trade is allowed, but experiences a reduced built-up if no trade is possible. In order to achieve its target domestically, nuclear, hydropower and solar PV are introduced

instead. With the allowance of trade, however, growth recovers in that region, which, although selling permits in the first periods, becomes an important purchaser at the end of the horizon.

The gas fuel cell still penetrates less than in the reference scenario. Without trade, its growth is significantly higher in NAM, ASIA and LAFM. With late full trade (after 2030) its role declines in all regions except the EEFSU. With earlier trade, the technology substantially rebounds in OOECD, EEFSU and ASIA.

Solar PV also penetrates in this scenario. Among the different cases, higher deployment occurs in the no trade situation. With all regions achieving their targets domestically, the technology experiences dynamic growth. With the allowance of trade its role is notably affected in all regions. Already in the full-trade-2030 variant the technology decreases its penetration noticeably. If trade is permitted earlier (2010), its growth is higher in ASIA, which as the main permits seller has an incentive to deploy low-carbon technologies, but diminishes even further in the other regions.

The wind turbine still penetrates along its maximum growth constraint in all regions.

In order to illustrate an interesting detail concerning the difference between a model with multi-regional spillover of learning and one without it⁹¹, Figure 122 presents an additional comparison. The outputs of learning electricity technologies in 2050 in the different regions are contrasted here for the Kyoto-trend and Kyoto-global trend cases when no emissions trade across regions is permitted. That is, the only link between them is the (here assumed full global) learning spillover.

Despite the fact that Annex I regions face the same constraint in both cases and are compelled to fulfil it with their own domestic mitigation efforts, the technology outcome is not the same in those regions for both cases. In the second case, the fact that non-Annex I regions also commit themselves to achieve reductions alters the dynamics of global diffusion of some of the learning technologies. In particular, solar PV penetrates in Annex I regions under the Kyoto global-no-trade scenario. Also, new nuclear, gas combined-cycle and the gas fuel cell alter their penetration as compared with the Kyoto-trend-no-trade one.

Of course, the effects of the spillovers in the technology choice depend also on the stringency of the constraint and the characteristics of the region(s) where it is imposed⁹². For instance, in this exercise, the imposition of the Kyoto-trend constraint on Annex I regions (without trade) stimulated the increase of output of gas combined-cycle in ASIA, as already described above. But, despite the full global learning spillover, such constraint was not enough to produce noticeable additional deployment of the other learning technologies in the developing regions compared to the baseline situation. In contrast, the fact that these regions face a reduction commitment in the Kyoto-global trend scenario produced a stronger stimulation of the penetration of several learning

⁹¹ That is the case, for instance, of a linear programming model, where the exogenous specification of cost trends for the technologies precludes such kind of interaction, or a model with learning where no spillover between regions takes place.

⁹² The effects are also a function of the magnitude of the spillover coefficients across regions.

technologies (or a larger de-stimulation as in the case of the advanced coal power plant) in Annex I regions as discussed above.

This effect cannot be taken into account in a conventional linear programming model. There, the technology mix in the Annex I regions would be bound to be the same in both cases because no interaction mechanism between regions would be present. This is an important point, because it implies that considering multi-regional learning represents an improvement in the modelling of technological change induced by environmental constraints. First, under the presence of learning mechanism, the imposition of environmental constraints can induce cost reductions (increasing competitiveness and likelihood of diffusion) of environmentally compatible technologies. Second, when spillover of such technological learning across regions is possible, other regions can benefit from the technological change stimulated by tighter environmental policies.

Thus, a model with multi-regional learning spillovers has a fundamental, although maybe still rudimentary and perfectible, mechanism that helps reflecting the possible response of accelerating technological progress (here represented as cost reductions) in low-carbon technologies in different regions of the world induced by stronger climate control policies in one of them. In fact, it has been argued that if some regions were to take the lead in the abatement efforts, in a globalised world this could change the perspectives of more environmentally compatible technologies in other regions as well. This could provide the leading regions with "first mover" advantages in terms of technological leadership and exporting capabilities and help the others to reach their own environmental goals at lower costs (Chua, 1999).

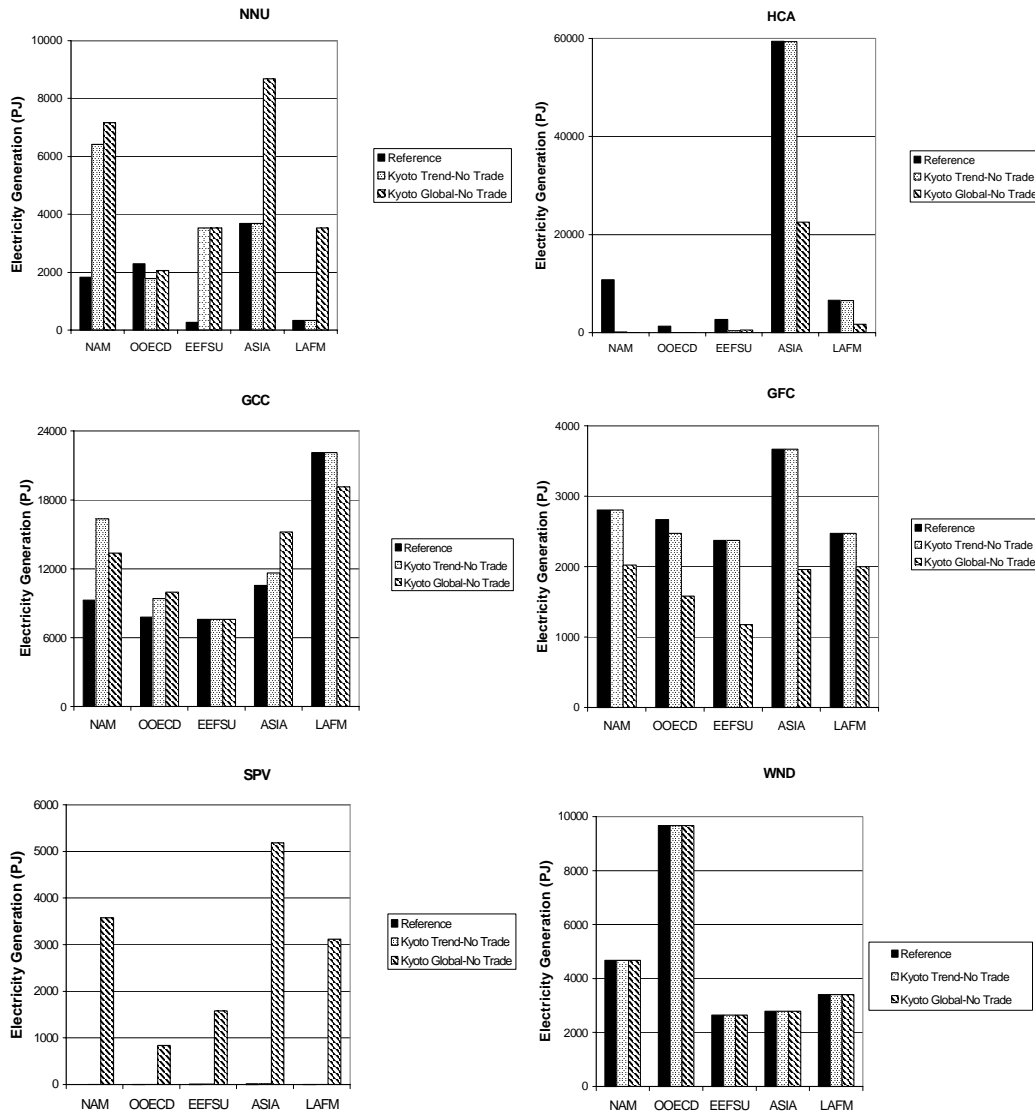


Figure 122. Electricity generation of learning technologies in 2050. A comparison between Kyoto-trend and Kyoto global-trend without trade cases. Global learning.

8.3 Sensitivity to the spatial learning spillover

The analysis above has assumed full spillover of learning at the global level. In this section the sensitivity of the results to different geographical configurations of learning is examined. Such kind of analysis had been already carried out in chapter 6, being shown that the scale at which the learning process is assumed to take place can affect significantly the results. Here, besides global learning, three additional scenarios are considered. In the first scenario, called Annex I/non-Annex I learning, two separate learning domains are specified: the Annex I group (i.e. NAM, OECD and the EEFSU) and the non-Annex I group (ASIA and LAFM). In the second one, labelled IND/EIT/DEV learning, three learning blocks are defined: Industrialised regions (NAM and OECD), economies-in-transition (EEFSU) and developing regions (ASIA and LAFM). Finally, a single-region learning scenario, with each region learning alone, is considered.

As before, those scenarios are arbitrary and may not reflect the real "topology" of the learning networks of the technologies affected, particularly in an increasingly globalised world where multi-national energy technology suppliers operate all over the world. Thus, they are applied here only with illustrative purposes. Still, such hypothetical learning configurations allow insights into the consequences of co-operative/non-cooperative learning for emerging technologies and the interaction between the multi-regional learning and emissions trading mechanisms.

The discussion has been concentrated on how the variation of the scale of learning affects the deployment of solar PV in the different regions under the Kyoto-trend scenario. For simplification it has been assumed that the same learning curves applied in the global learning situation are valid for the different learning scales. Also, only a single learning curve is specified for a given learning domain and all the technologies are considered to have the same learning scale.

8.3.1 Spillover coefficients

Before proceeding with the presentation of the results, some general comments regarding the description of a given configuration of international spillovers of learning are necessary. The notion of spatial spillover coefficients is outlined to clarify the specific configurations analysed here. One could think of expressing the degree of learning spillover from one region to another in terms of spillover coefficients. A spillover coefficient ($\sigma_{i,j,t}$) represents the fraction of the installations made in a given region j that is added to the cumulative capacity in another region i , in order to compute the corresponding investment costs⁹³. That is, the fraction that learns following the experience curve in the region i .

In the general case, assuming that a given technology possesses a particular learning curve in each geographical region, the cumulative capacity ($C_{k,i,t}$) of the technology k in the region i at the time period t can be expressed as:

$$C_{k,i,t} = C_{k,i,0} + \sum_{\tau=1}^t \sum_{j=1}^N \sigma_{i,j,\tau} * INV_{k,j,\tau} \quad (46)$$

With:

k :	Technology index
i,j :	Region index $i, j \in \{1, \dots, N\}$
t, τ :	Time indexes
$C_{k,i,0}$:	Initial cumulative capacity of technology k in region i
$INV_{k,j,\tau}$:	Investments in technology k in the region j for the period τ
$\sigma_{i,j,\tau}$:	Spillover coefficient between region i and j for the period τ .

Generally, the spillover coefficients are time-dependent. That is, the learning "topology" and the strength of the corresponding linkages between regions may evolve in time. Here, for simplicity they are considered time-independent.

⁹³ In the text, the notion of scale of learning is still used to describe the particular configurations examined here. However, the notion of spillover coefficients allows a more general description.

A particular set of spillover coefficients represents a specific learning "topology". For instance, if $\sigma_{i,i}=1$ and $\sigma_{i,j}$ is zero for $\forall i \neq j$, then a single-region learning configuration is specified. That is, all the investments made in a given region j contribute to the learning curve specified for that region. In such case, N experience curves are necessary in the model for a given learning technology. Also, if for a given region I , $\sigma_{i,j}$ for $\forall j$ equal to one, then the totality of investments made in all regions in a given technology contribute to the cumulative capacity of region i . Owing to the condition set above, all other $\sigma_{i,j}$ are zero for $i \neq I$. In such case, full spillover at the global level takes place and a single learning curve is required⁹⁴.

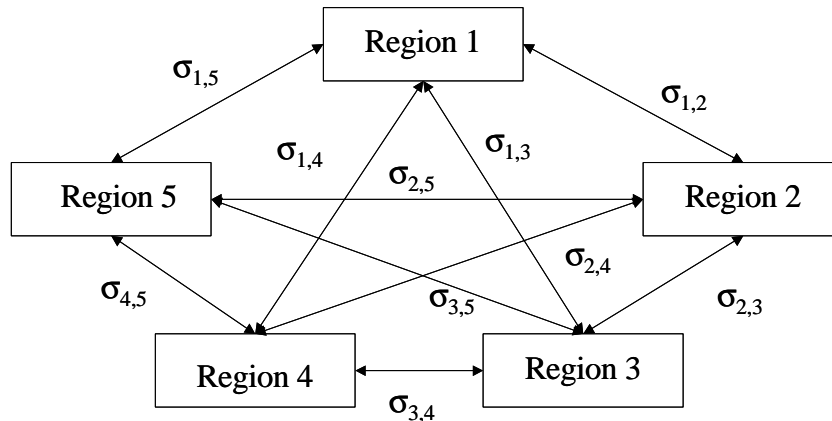


Figure 123. Multi-regional spillover of learning.

Turning now to the specific illustrative configurations applied in this analysis. Assigning a number to each region (NAM=1, OECD=2, EEFSU=3, ASIA=4, LAFM=5), the "topologies" examined here can be described in terms of the spillover coefficients defined above as follows:

- Global learning: $\sigma_{1,j}=1 \forall j \in \{1,..,5\}$, $\sigma_{i,j}=0$ for all other combinations.
- Annex I/non-Annex I learning: $\sigma_{1,j}=1$ for $j \in \{1,2,3\}$, $\sigma_{4,4}=1$, $\sigma_{4,5}=1$, $\sigma_{i,j}=0$ for all other combinations.
- IND/EIT/DEV learning: $\sigma_{1,1}=1$, $\sigma_{1,2}=1$, $\sigma_{3,3}=1$, $\sigma_{4,4}=1$, $\sigma_{4,5}=1$, $\sigma_{i,j}=0$ for all other combinations.
- Single-region learning: $\sigma_{i,i}=1$, $\sigma_{i,j}=0 \forall i \neq j$.

That is, the spatial learning configurations analysed here consider that spillover between two given regions is either full or it does not exist (i.e. $\sigma_{i,j}$ assume values of one or zero) and, as mentioned above this will not necessarily be the real case. But, using models of the type applied here the effects of many other different sets of spillover coefficients could be examined. For instance, it could be explored how a particular hypothetical

⁹⁴ In the analyses performed in this document, where as simplification a single learning curve is specified for a given learning domain comprising one or several geographical regions, the denomination global learning has been used for this situation. But, actually one could think about a condition where the spillover occurs at the global scale but it is not necessarily full. That is, where learning processes in all regions are "interconnected" to each other, but only a fraction of the installations in each of them contributes to the global learning (i.e. $\sigma_{i,j} \leq 1$). The representation of such condition, however, would require the specification of separate learning curves for the different geographical regions and is not undertaken here.

"learning strategy", where learning links between different countries or regions are established, could affect the diffusion of a given technology. Also, future work should be devoted to establish whether an empirical estimation of such coefficients for specific technologies could be undertaken and/or to develop criteria for supporting the corresponding assumptions in the models.

8.3.2 Deployment of solar photo-voltaics

The example presented here concerns the deployment of solar photo-voltaics in the reference and Kyoto-trend scenarios when applying the different learning scales described above. Figure 124 presents the electricity generation of this technology in 2050 in the different regions. The global output is also shown. Under the particular conditions assumed in these model runs, solar PV is a marginal technology and as such is strongly affected by the variation of the learning scale.

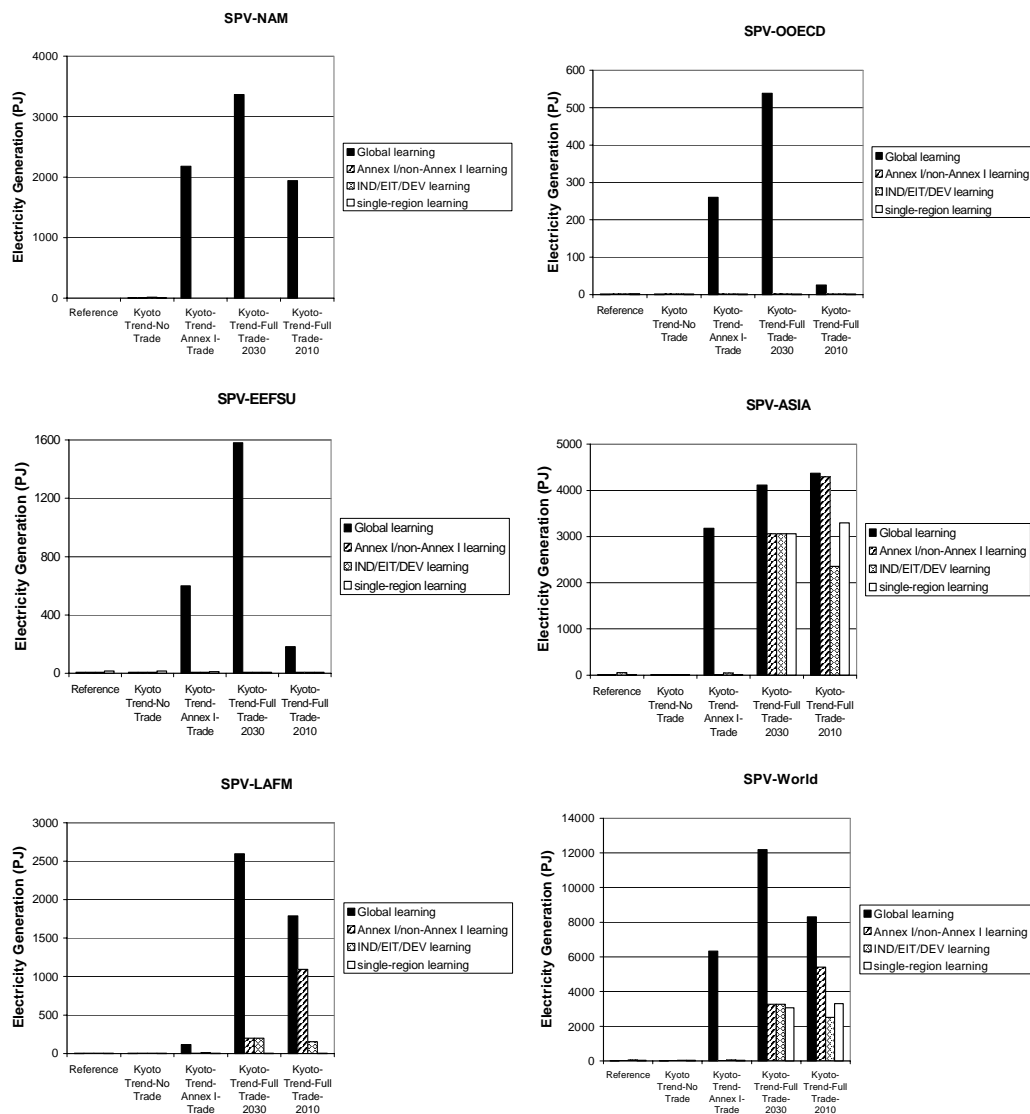


Figure 124. Regional electricity generation of solar photo-voltaics in the year 2050 under different scales of learning. Reference and Kyoto-trend scenarios.

The three Annex I regions show a similar pattern of installations. The technology is introduced in significant amounts only under the global learning situation. Otherwise, it remains practically "locked-out". Under global learning, as already discussed above, installations take place exclusively under the Kyoto-trend scenario and only when (Annex I or full) trade is permitted. In those cases the technology is deployed in all regions. The highest penetration is achieved in the Kyoto-trend-full-trade-2030 case. There, on the one hand, Annex I regions are compelled to vigorously stimulate early learning in the first periods because trade with developing regions can be made only later in the time horizon. On the other hand, early deployment also takes place in the developing regions, which are due to become permit sellers later on. Thus, as each region profits from the learning process in the others, both processes cross-enhance each other, strengthening the penetration, and the technology is able to reach a sizeable expansion in all regions. With the allowance of an earlier full trade umbrella, the capacity built-up in Annex I regions is discouraged and lower penetration is reached in all regions, with the exception of ASIA, which is the predominating permits seller in this situation.

But, with the reduction of the learning scale, Annex I regions cannot benefit from the cost reductions caused by the deployment in non-Annex I regions, where higher production potential is at hand. As a result, the technology is no longer attractive in Annex I regions. Other technologies take the lead. Among others, new nuclear power plants have a higher output.

Before continuing with the examination of the deployment in the non-Annex I regions a remark is necessary here. In this particular exercise the competition between solar PV and the new nuclear plant plays an important role in the final outcome. Hence, it is important to notice the differences between these two learning technologies. Solar PV has very high specific investment costs at the starting point of its learning curve, but it exhibits high learning potential (i.e. a progress ratio of 0.81). On the other hand, the new nuclear plant has a lower starting point (although its costs are still high) but its learning potential is not very high (i.e. a progress ratio of 0.96). Thus, solar PV needs a higher amount of cumulative learning investments in order to become competitive and it is, consequently, more sensitive to the shrinking of the spatial scale of its learning process. Therefore, although when the conditions change in favour of low-carbon technologies (i.e. imposition of a CO₂ constraint) opportunities for both of them exist, only when sufficient potential for cost reductions of solar PV is accessible it will become attractive. That is, for example, the case in the global spillover situation. In other circumstances new nuclear is more likely to have the advantage.

Also, in the non-Annex I group installations take place only when emissions' trading is allowed. That is, the possibility of selling permits to the carbon-constrained Annex I regions stimulates the deployment of low-carbon technologies, solar PV among them, in these regions. With global spillover of learning the technology is introduced both when Annex I-trade or global trade are possible. The penetration in these regions in the Annex I-trade case is a consequence of the global spillover effect. In such situation, growth is stimulated in the EEFSU region, which sells permits to the industrialised ones. As the system is allowed to benefit from the global learning situation, this triggers installations in the other four regions in order to take full advantage of the learning potential

available⁹⁵. In the full trade case the introduction in the non-Annex I group is, as mentioned before, the result of the incentives to sell permits to the Annex I regions.

The technology still remains relatively attractive when the learning scale shrinks. This is basically due to installations in ASIA and, to a much lower extent, in LAFM. However, with reduced scales of learning it is installed in these regions only when full trade is allowed. That is, only when an incentive to sell permits to the Annex I regions exists. Under the no trade or Annex I-trade situations the technology is not introduced. In such circumstances none of the two mechanisms of interaction between the Annex I and non-Annex I groups considered here, namely learning spillover and trade, is acting. That is, the two groups are "decoupled" from each other and this strongly undermines the diffusion process in all regions.

In ASIA, as the scale of learning gets smaller the technology's penetration experiences a sizeable diminution but it continues to be an economic option as the region possesses the highest solar electric potential and, being a major seller of CO₂ permits, has an incentive to deploy low-carbon technologies.

In the Kyoto-trend-full-trade-2030 case the output of solar PV in ASIA remains the same for the three additional learning scales, but it is lower than in the global learning case. Under these restricted scales of learning the region is selling more permits at the end of the horizon than in the global learning case, particularly to the EEFSU and OECD regions. Thus, despite the reduction of the learning scale there is still incentive to build solar PV capacity.

In the Kyoto-trend-full-trade-2010 case the deployment diminishes slightly with Annex I/non-Annex I learning, declines much further under the IND/EIT/DEV configuration but rebounds again with single-region learning. Interestingly, the electricity generated by solar PV is smaller in the IND/EIT/DEV learning case than in the single-region or Annex I/non-Annex I ones. This happens despite the fact that in the Annex I/non-Annex I and IND/EIT/DEV situations the learning domain remains the same for the technologies deployed in ASIA.

Such behaviour deserves some elaboration. The changes in the learning scale from the Annex I/non-Annex I situation to the IND/EIT/DEV one basically affect the Annex I regions because the learning potential of their low-carbon technologies is smaller (the non-Annex I regions retain the same learning domain). This discourages the installation of low-carbon technologies there. Specifically, the model finds more economic for the NAM region to buy more permits here than under other scales of learning and this results, among others, in a lower penetration of the new nuclear power plant there. The higher volume of permits is provided mainly by ASIA and, to a lower extent, by LAFM. But ASIA now favours conventional and new nuclear power plants instead of solar PV.

⁹⁵ As already mentioned in chapter 6, in order to understand the results, in particular the "abrupt" changes in the penetration of the solar PV from one case to the other, it is important to bear in mind the way the learning mechanism operates in the model. Although other factors also intervene, the potential available for costs reductions strongly influences the outcome. If enough learning potential is at hand, the model may choose to introduce the technology as much as possible trying to exhaust it. But, if such learning potential is not sufficient to render it cost-effective, it could leave the technology "locked out".

That is, although the interaction is complex and a one to one correspondence of the effects cannot be ensured because other adjustments are involved, the model appears to prefer installing new nuclear capacity in ASIA and LAFM, given that the learning potential of the technology there is higher, and let NAM buy the corresponding emission credits, than building new nuclear capacity in NAM, where only the learning potential of NAM and OECD together can be "tapped". In addition, under these particular conditions it results more attractive to choose nuclear than solar PV in the selling regions.

In the single-region learning case not only the permit buying regions have less learning potential but the selling regions too. Thus, the competitiveness of ASIA as a permit seller is also affected. The total volume of permits bought by NAM decreases and, thus, the volume of permits sold by ASIA does so as well. In such circumstances, the electricity generation from new nuclear power plants recedes in ASIA and solar photo-voltaics manages to rebound to some extent, despite the fact that its learning domain is confined only to "domestic" installations in the region.

That is, in this particular case, putting the two developing regions together in a joint learning domain while the Annex I regions act as two blocks (IND and EIT) affects the ranking of technologies and the amount of permits bought/sold in each of them in such way that solar PV loses competitiveness against nuclear power plants. In contrast, when having each region learning separately, the model finds more effective to install new nuclear capacity domestically in NAM buying, in consequence, less permits from abroad. This has as effect a lower installation of new nuclear in ASIA and allows solar PV to revive.

In LAFM the reduction is much more substantial when the learning scale is reduced, compared to the global learning case. In the Kyoto-trend-full-trade-2030 case the output of solar PV is already substantially reduced with Annex I/non-Annex I or IND/EIT/DEV learning and it dwindles under single-region learning. The Annex I/non-Annex I and the IND/EIT/DEV spatial configurations of the learning networks result in a higher volume of permits sold by LAFM, but favour the installation of new nuclear power plants (which takes place both in LAFM and ASIA in order to benefit fully from the learning potential) and gas fuel cells instead of solar PV. The single-region learning configuration affects the attractiveness of LAFM as permits provider. The region sells less permits and, therefore, the installations of both solar photo-voltaics and new nuclear alike are affected.

In the Kyoto-trend-full-trade-2010 case the decrease is less significant for Annex I/non-Annex I learning but it is very strong for the IND/EIT/DEV situation and under single-region learning the technology is again "locked-out". With Annex I/non-Annex I learning the region increases slightly its permit sales, but the installation of gas fuel cells and conventional nuclear is favoured. Without full global spillover of learning solar PV results less attractive. A further increase of permits sales occurs in the IND/EIT/DEV configuration, as mentioned above when discussing deployment in ASIA. But, despite this, with its learning domain confined to the developing regions solar PV does not result attractive and the gas fuel cell, conventional nuclear and hydro increase their output instead. With single-region learning, as the region reduces its CO₂-permits sales, the technology is not introduced.

It is important to notice here an interesting aspect of the intertwined influence between learning and emissions trade, the two multi-regional interaction mechanisms considered here. Owing to the action of emissions trading, changes in the learning topology of the low-carbon technologies available in a given region, which make it more prone to buy/sell permits, become also influential in the final technology choice in other regions.

To summarise, Figure 125 presents the comparison of the electricity generation of solar photo-voltaics for the year 2050 in the Annex I and non-Annex I groups under the different scales of learning examined here. The different dynamics of the technology's penetration in both groups can be observed. As complementary information Figure 126 presents the corresponding electricity generation of the new nuclear power plant in both groups. However, no detailed discussion of the deployment of the latter technology is made here.

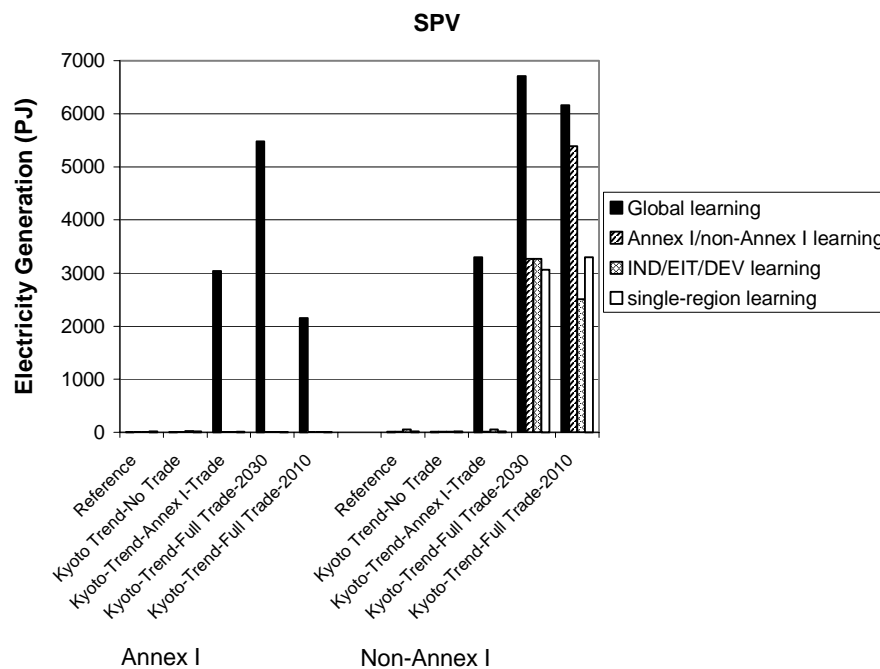


Figure 125. Comparison of the electricity generation of solar photo-voltaics in Annex I and non-Annex-I groups of regions for the year 2050. Different scales of learning. Reference and Kyoto-trend scenarios.

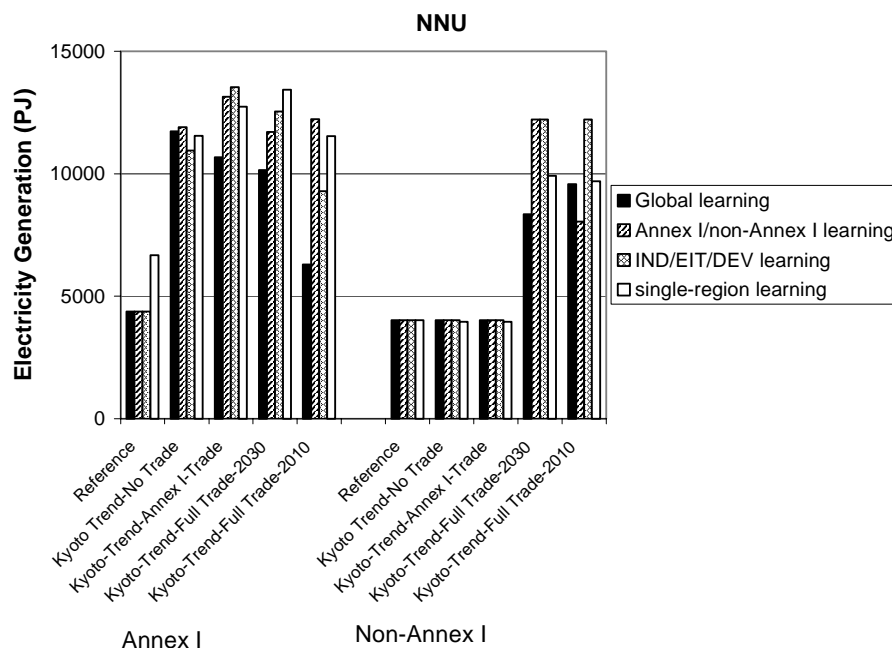


Figure 126. Comparison of the electricity generation of new nuclear power plants in Annex I and non-Annex-I groups of regions for the year 2050. Different scales of learning. Reference and Kyoto-trend scenarios.

On the whole, the solar PV technology benefits from a larger learning domain. Imposing restrictions on the scale of learning affects its diffusion substantially. This is particularly so in Annex I regions, which do not possess large solar electricity potentials, but it becomes apparent also in non-Annex I regions, despite having a larger solar resource at their disposal. The competitiveness of the photo-voltaics option suffers when both groups are left only with their own learning opportunities or when a further fragmentation of the learning network occurs, leaving smaller groups or single regions learning alone. As for the influence of emissions trading, its allowance stimulates the deployment of this otherwise marginal technology, but different trading modalities combined with diverse scales of learning drive to various degrees of penetration. Specifically, Annex I-trade only drives to installations when full spillover of learning at the global scale is possible. Permitting full trade provides an effective stimulus for the penetration of the technology in the non-Annex I regions, although the magnitude of such penetration is affected when the learning scale shrinks.

It is not easy to derive a straightforward conclusion about the mutual influences between the learning scale and the trade and their impact on the final outcome. The interactions are complex and appear case and technology dependent. But, basically, the reduction of the learning scale changes the ranking of technologies in the different regions altering the technology choice and the amount of permits bought/sold by them, and the consequences of those changes depend on the modality of the trading mechanism and the stringency and location of the emission constraint.

The configurations examined here are only hypothetical. Nonetheless, they illustrate the importance of exploring the influence of different "topologies" of multi-regional

learning networks in the model outcome. For instance, the effects of bilateral or multilateral learning partnerships could be examined within this framework.

A deeper examination of this issue is necessary and the many factors that could play an important role in shaping the learning networks should be examined to get a clearer picture⁹⁶. For instance, it is important to take into account that trade relationships (not CO₂ trade but normal trade of goods and services across regions and countries and the associated knowledge transmission) and foreign direct investments (FDI) appear to play an important role as "non-conventional" mechanisms of technology transfer (Chua, 1999) and could help in the diffusion of clean and more efficient technologies. This applies, for instance, to the action of multinational energy technology suppliers, more and more common in a globalised world. Also, the industrialised regions, possessing technological expertise and benefiting from "first mover" advantages, could become the main exporters of those "green" technologies to other regions, thus benefiting from "learning-by-doing" effects in manufacturing processes. Therefore, learning will probably not take place on an isolated basis in each region. But, nonetheless, setting in motion a truly effective and meaningful international learning process requires other factors, such as building local capabilities and strengthening local science and technology systems, essential for achieving the successful diffusion of new cleaner and more efficient energy supply and demand technologies, particularly in the developing world.

Also, even under the effects of those international interactions, which do not depend directly from the enforcement of a globally co-ordinated climate change policy, the signals given by a CO₂-permits market could affect technology diffusion patterns. If the price signals provided by an emissions trading system where cheap mitigation options are available were too low, this could exert a negative impact on the development and diffusion of more radical emerging innovations. Therefore, government intervention and international partnerships are required to foster learning and adoption of cleaner and more efficient energy supply and demand technologies around the world. Still, the role of emissions trading as stimulus/obstacle for the innovation process is not fully clear and additional effort should be undertaken to clarify the issue.

8.4 Conclusions

In this chapter, an indicative post-Kyoto analysis has been performed using a five-region compact "bottom-up" MARKAL model (with inelastic demands) of the global energy system. The response of the model to Kyoto-like CO₂ emission constraints is analysed for a scenario of gradual economic growth and corresponding energy requirements. Emphasis has been given to the contribution that the global electricity generation system may have in a future CO₂-constrained world. Such analysis has been carried out considering endogenous technological learning for several electricity generation technologies.

⁹⁶ Clearly, although in the model the learning networks are schematically represented in a stylised way through the spillover coefficients, the conformation and evolution of such networks in the reality are much more complex. Thus, case studies of the "innovation geography" of different technologies or groups of technologies are necessary both to support the model's assumptions and to get insights into the driving forces of the spatial-temporal diffusion process.

The discussion has been centred on a Kyoto trend scenario with emission constraints imposed only on Annex I regions. The fulfilment of such abatement target under different modalities of emissions trading is examined. As a complement, the response of the system under a Kyoto global trend constraint has been investigated. With developing regions assuming CO₂ reduction targets later in the horizon, such scenario provides a stronger decarbonisation of the energy system. The comparison of the deployment of learning technologies under this and the Kyoto-trend scenario allowed identifying interesting aspects of the response of the model in the presence of multi-regional learning spillovers.

The analysis confirms that, as electricity, a clean and flexible final energy carrier, follows a vigorous penetration in diverse end-use sectors and increases its share of the final energy mix, the decarbonisation of the generation system is bound to play an important role in a global CO₂ mitigation strategy. Such decarbonisation process under a Kyoto-like target could offer opportunities for the penetration of less carbon-intensive and more efficient emerging generation technologies. Results remain, of course, highly dependent on the assumptions. But, more importantly than the numbers and assumptions here, the dynamics of learning technologies in response to changes in CO₂ constraints, trade modalities and geographical scale of the learning process have been examined.

In particular, it is observed that under the presence of multi-regional learning spillovers in the model, carbon abatement activities in a given region stimulating technological change, here represented as costs reductions, of low-carbon technologies may foster their diffusion also in other regions, even in those that do not face an emissions reduction commitment. Such induced technological change may produce positive effects in terms of system costs and emission profiles in those regions. The magnitude of such inducement effect depends, of course, upon many factors but its presence is an indication of the possible beneficial impacts that "first mover" actions may have on the overall carbon mitigation in the global energy system.

Also, the introduction of multi-regional technological learning spillovers provides a fundamental, though still perfectible, mechanism to represent environmentally induced technological change in the model.

In addition, although all the caveats concerning the estimation of CO₂ abatement costs with "bottom-up" models are applicable here (Wilson and Swisher, 1993, Jochem et al., 1999) and the limitations of this particular analysis must be taken into account, some insights can be gained concerning the costs of compliance of a Kyoto-trend target. The fulfilment of such target, with emission caps imposed on Annex I countries, appears very costly and not particularly effective in achieving a significant long-term diminution of the CO₂ emissions from the global energy system. However, the analysis shows that international co-operation, here represented as emission trading, which increases the where-flexibility of the mitigation, may improve substantially the cost-effectiveness of the abatement actions. In particular, involving developing countries in the trading system may provide access to cheaper mitigation options, helping Annex I countries to reduce their costs of compliance while providing non-Annex I regions with an stimulus to decarbonise their own energy systems.

Yet, many issues remain open regarding the implementation of such international collaboration in the climate change context and recent events have already shown that many obstacles are still to be solved before meaningful agreements can be reached (Pronk, 2001). In particular, although it appears to be sensible bringing developing countries in a strategy for curbing GHG emissions, such undertaking raises a number of implementation issues (e.g. equity, development, technology transfer, monitoring and compliance etc.) that must be addressed, and whose discussion remains outside the scope of this work. However, when examining the issue in the context of the role of technological change in curbing emissions, it becomes evident that a meaningful cooperation requires a sound stimulation of the technological learning of low-carbon technologies if the global energy system is to shift away from the fossil fuel regime in the long run. To be effective, such stimulation must take place at the local, regional and global levels both through government and business RD³ partnerships.

Multi-regional interactions are very important for technology diffusion. Following work in chapter 6, interactions between trade of emission permits and learning have been studied here. The main findings confirm the conclusions obtained previously but some additional insights are gained. Different modalities of trade have been examined here. The role of emissions trading in stimulating/hindering technological learning appears complex and dependent upon many factors. As a rule, the cheaper mitigation options brought about by the trading mechanism tend to produce a disincentive to deploy low-carbon technologies in permit-buying regions. But, on the other hand, trade stimulates their penetration in (potentially) selling ones. The final effects are highly dependent on the configuration of the learning and trading networks, the magnitude of learning spillover between regions and the level of the carbon constraint imposed.

Of course, changes in the spatial configuration of those networks along the time horizon have also noticeable impacts. Here, as an example, a later inclusion of developing regions in the trading system is analysed, in order to determine how such delay affects the "triggering" of the learning mechanism of electricity generation technologies. In those experiments, within a perfect foresight modelling framework, it was observed that delaying the availability of cheaper options in other regions could keep learning processes going on in the constrained regions. Such processes have influence, through spillover effects, on the technology choice of the permit-selling regions as well. By contrast, an earlier global trade may hinder learning processes in constrained regions with expensive mitigation measures but it may foster them in the selling regions. This can drive, provided the existence of learning spillover, to deployment of such low-carbon options also in the constrained (buying) regions. The final outcome depends, among other things, on the relative weight of these counteracting forces.

Nonetheless, the risk still exists that the availability of those initially cheap abatement measures drives to technological choices that "lock" the system into the current fossil trajectory, making difficult the long-term transition towards a different technological regime, necessary for achieving further and more radical mitigation targets (e.g. fuel switching from coal to natural gas power plants could hinder the introduction of other electricity generation options such as renewables). Or, said in another way, that the price signals emitted by the permit trading system may not be sufficiently high to trigger the necessary early technological learning. But, although the evidence presented here is not conclusive, the exercise reveals the fact that trade effects on energy innovation do

not necessarily have to be negative. Even in the cases when the trade configuration reduces the incentives to learn, the model still finds cost-effective to stimulate early learning of low-carbon technologies, although the process occurs at a lower scale.

In addition, the influence of the "topology" of the multi-regional learning network on the competitiveness of the learning technologies is examined with some examples. Here only some very specific configurations of learning spillover have been examined, either allowing the different regions to fully benefit from the learning potential in others or completely precluding them to do so. Such changes in the learning configuration, which basically shrink or expand the spatial domain of the learning process, alter the regional ranking of technologies and, consequently, the balance between domestic mitigation measures and transactions (sales/purchases) in the permits market for the different regions, among others. The interaction between different learning and emissions trading networks appears as an important determinant of the diffusion (or not) of emerging low-carbon technologies in a CO₂-constrained world. The relationships are, however, complex and the effects of learning spillovers should be analysed in more detail. Many other possible combinations of technology spillover linkages across regions could be possible and following this approach their effects can be explored.

In this analysis only the impact of learning in electricity generation technologies has been considered. Further work must be devoted to consider learning in other energy chains and to incorporate interactions within and between technological clusters. This would enable conducting a more comprehensive evaluation of the effects of technological learning in the global energy system on the costs of GHG mitigation strategies. Of particular importance appears to take into account learning in highly efficient end-use devices⁹⁷, in order to improve the estimation of the potential contribution of energy efficiency to a greenhouse gases mitigation strategy.

An additional important aspect of future work regarding the effects of learning spillovers would be to compare the insights provided by the model applied here with other analyses and approaches. Of particular interest appear to be the results of some experiences with "top-down" models. Buonanno et al. (2000) present a modified version of the RICE model (Nordhaus and Yang, 1996), endogenising technical change in form of a general R&D knowledge stock. Game theory is applied to solve a non-cooperative game between regions. That is, regions act as separate actors optimising their own strategies with respect to those of other regions. The level of R&D carried out by a given region is affected by the presence of environmental policies. Those modelling exercises revealed the possibility that, in such competitive environment, the presence of R&D spillovers, although producing positive effects in the level of emissions and corresponding abatement costs due the diffusion of R&D worldwide, reduced the incentives to carry out strategic R&D in the individual regions. That is, the possibility of free riding makes some participants become reluctant to share their knowledge stock and, therefore, they diminish their amount of R&D.

In the "bottom-up" model applied here, however, technical change is endogenised through the learning effects due to capacity deployment of explicit technologies in the

⁹⁷ Empirical evidence of learning in these technologies exists. See, for instance, Iwafune (2000) for a case study of compact fluorescent lamps or Lawitzka (1999) for solar-heated swimming pools. However, more case studies should be carried out in order to support the assumptions on learning in the models.

market. The effects of R&D efforts, the other main learning channel, are not incorporated. Also, a "monolithic-actor " type of optimisation takes place. That is, the model finds the least-cost solution for the whole set of regions. Under such conditions, higher levels of learning spill-over across regions are desirable, because they entail the possibility of making the technology even cheaper as one region may benefit from the cost reductions caused by capacity accumulation in other region. Further work should be devoted to scrutinise carefully the possible discrepancies in the results and policy insights obtained with these two modelling approaches concerning the role of learning spillovers. Also, it would be very interesting to explore the possibility of combining them.

9. Conclusions

The study of the possible future structural transitions of the global energy system and the assessment of the role that emerging energy technologies may play in such transitions are complex tasks involving the examination of interactions between a number of technical, economic, environmental, social and political driving forces. The dynamics of technology constitute a central factor in shaping such future trajectories. It is necessary to understand the variables that are likely to influence its evolution and the actions to be taken in order to ensure more productive, efficient, economically viable, environmentally compatible and safe energy systems.

Technology is endogenous to the social system where it evolves. Thus, technological and social dynamics are intrinsically linked and a number of interactions and mutual influences take place. New structures, needs and exigencies of the economy, and the society as a whole, are powerful change-inducing forces fuelling technological change. In its turn, technological change enables new possibilities in social and economic activities and has an impact on societal transformations. The global energy system is, of course, no exception in this intertwined evolutionary process.

Important as it is, technology dynamics have not been adequately represented in the energy-economy modelling approaches customarily available. A series of driving factors, concerning the cost/performance evolution of technologies, their diffusion patterns, the cross-enhancing interactions between them, the effects of R&D spending, the inertia and capacity of change of the system, among others, have been handled in an exogenous manner or not considered at all in the traditional modelling approaches. Technological change, however, is not an autonomous but an endogenous process, where those and other forces intervene and influence each other. Therefore, the evolution of the technologies should not be exogenous but dependent upon other parameters and variables in the models. Thus, there exists a necessity for a better treatment of technological dynamics in energy decision-support frameworks. Basic mechanisms and patterns of change must be adequately reflected in the models in order to perform meaningful analyses and derive sensible policy insights.

This dissertation deals with the incorporation of one of such basic mechanisms in energy optimisation models: Technological learning. Learning constitutes a key driving force of technological progress, playing an important role in cost/performance improvement of technologies and stimulating the competition and continuous substitution between them in the marketplace. Uncertain technological learning processes have a significant influence in shaping the path the global energy system follows and, therefore, influence the subsequent economic, social and environmental impacts associated to the realised trajectory. Different competing technological paths in the energy system will be either promoted or hindered by their respective opportunities to acquire and accumulate knowledge within the constantly evolving social learning networks (Martin, 1996).

The endogenisation of technological learning represents an advance towards a more comprehensive framework for the treatment of technological change in energy optimisation models. Here, experience curves, an empirical manifestation of

technological learning, have been incorporated in two linear programming "bottom-up" energy systems models: MARKAL and ERIS. The curves reflect the fact that some technologies experience declining costs as a result of increasing adoption into the society due to the accumulation of knowledge through, among others, learning-by-doing, learning-by-using and learning-by-interacting processes. Although the curves have been applied here only for investment costs using cumulative capacity as a proxy for the cumulated knowledge, in principle nothing precludes their application to other performance indicators (e.g. O&M costs or efficiency) or the use of other variables to measure the associated cumulative knowledge.

Learning constitutes an increasing returns mechanism and therefore leads to a positive feedback effect, which introduces interesting patterns of response in the models. The behaviour of the two models when incorporating such increasing returns mechanism is examined here with a number of illustrative analyses. The methodological and policy insights obtained from those exercises are discussed. The analyses provide evidence of the critical role that the representation of the technological variable plays in the model outcome and, therefore, in the policy insights that can be derived from the modelling exercises.

The analyses have shown the significant influence of endogenous technological learning in the structure of the least-cost energy system obtained in the model results. New, initially expensive technologies, hardly considered by the linear programming model, are introduced to the solution as a consequence of the endogenous cost evolution. For the perfect foresight model it can result cost effective to make higher early investments in initially expensive technologies if they exhibit sufficient cost reduction potential along the time horizon.

As the cost evolution is determined by the experience curve, early investments are a necessary condition for the corresponding cost reductions to be realised in the model. Up-front investments are made, allowing those technologies to accumulate the experience they require to become competitive in the long run. As in the reality new technologies will become competitive only if experience with them is possible, the modelling results point out the need for early investments on emerging environmentally compatible technologies, both in R&D and niche markets, in order to ensure that they move along their learning curves and reach long-term competitiveness with well-established technologies.

Thus, the technological learning concept conveys an important policy message regarding energy technology dynamics: Sustained efforts in research, development, demonstration and deployment (RD³) are required in order to stimulate the cumulative and self-reinforcing processes that drive to progress and diffusion of emerging technologies. Progress will not occur automatically. It requires continuous action. In particular, to achieve cost reductions, critical to ensure competitiveness, the markets constitute the ideal "playground". Market experience plays a very important and decisive role in the learning process.

The conceptual model of the learning curve contributes to the definition of strategic policy measures regarding the stimulation of environmentally compatible technological change, helping to assess opportunities and requirements for promising, clean and more

efficient energy technologies and to estimate their maturation costs. In such sense, it provides a useful tool, both to guide the conformation of portfolios of technologies whose future potential justifies current support and to monitor the stages at which such support should be provided and/or withdrawn.

As a number of different promising alternatives may be available at the starting point and uncertainty exists, among other factors, in their improvement potential and possible future impacts, it seems advisable for the portfolio to be a diversified one, in order to avoid a premature "pick-up" of the winners, thus providing hedging against uncertainties in the technology development and allowing maximum flexibility in reshaping decisions with a minimum regret.

Concerning a number of energy technology policy issues, the modelling results suggest significantly different actions than what conventional wisdom may indicate, and alter also the perception of the timing and costs of such policies. For instance, when examining strategies to mitigate environmental impacts from the energy systems (e.g. climate change), an endogenous dynamics of technology, which recognises the gradual and cumulative nature of technological change, favours early action in order to stimulate the technological learning necessary to improve costs and performance of new, more environmentally compatible and more efficient technologies. On the contrary, an exogenous dynamics favours delaying any intervention until more cost-effective, cleaner and more efficient technologies become available. The latter approach, however, ignores the fact that technological progress does not occur as "manna-from-heaven" and, therefore, is not able to capture the RD³ investments that are indispensable to make the technologies advance and attain competitiveness in the marketplace.

In addition, the presence of endogenous technology dynamics tends to provide lower estimates of the costs of achieving such mitigation. Also, with an earlier introduction of cleaner learning technologies, the models may produce lower emission profiles. Early action translates into long-term economic and environmental benefits.

Thus, models with endogenous learning draw attention to the necessity of being aware of the role of technology dynamics when discussing strategies for achieving environmental goals for the global energy system and, in particular, of taking into account the technological "lock-in" phenomenon. In order to do so, international agreements to mitigate negative environmental impacts of energy production and consumption should include instruments of compliance designed to encourage technological progress to shift away from the fossil fuel regime and to exploit the "lock-in" effect in favour of cleaner and more efficient technologies (McDonald, 2000).

At this point it is important to examine the results of the models in a more ample and realistic perspective. Despite the somewhat optimistic results concerning the penetration of new technologies that can be obtained with perfect foresight cost-optimising models that incorporate the learning mechanism, it is evident that competition against well-established mature technologies will not be easy for emerging, more efficient and less polluting, but more expensive alternatives, particularly in the increasingly liberalised energy markets, where short-term profitability criteria drive the technological choice (IIASA-WEC, 1998, Grubb et al., 2000). Moreover, one has to recognise that

engineering-economic models, such as those applied here, ignore a number of organisational, institutional, behavioural and social obstacles (and opportunities) for the diffusion of new technologies that, when considered, may alter the attractiveness of the options identified by the models (for a discussion see, for instance, Jochem, 1999).

Clearly, a comprehensive analysis should include those aspects and many more. Here, however, emphasis has been given mainly to modelling issues. Nonetheless, and more importantly than the numbers and assumptions made here, the modelling exercises deliver clear and valuable insights into the importance of the learning process and the need of pursuing its early stimulation. But, of course, models constitute only a guide to the decision-making process and what becomes the real policy issue is the creation of the conditions to make the learning process effectively happen for clean and more efficient energy supply and demand technologies in the global marketplace.

Following the line of reasoning provided by the models with endogenous learning, it becomes clear that if they are to play a significant role in future energy markets, emerging environmentally compatible technologies will require investments, both in R&D and niche markets, to foster their development and diffusion. Experience with them will be a key, enabling factor in order to ensure competitiveness. But, in order to be able to gather such experience, critical to set progress in motion, adequate technical, financial, institutional, market etc. instruments must be in place. Those instruments must be conceived in awareness of the technology dynamics that takes place in the energy systems and be designed to take advantage of such dynamics. For instance, in order to take full advantage of the forces behind the learning process, to encourage the best-performing systems to be diffused and to consolidate long-term markets, technology policy instruments may be required to provide specific incentives to production (and not only installations) from new cleaner electricity supply technologies (Loiter and Norberg-Bohm, 1999).

In summary, their successful introduction, necessary to guide the system towards a sustainable trajectory, requires strategies to create incentives for innovation and learning at multiple technological, social and institutional levels. This drives us to a relevant policy guideline. Learning is a network phenomenon. Thus, its successful stimulation is linked to the creation and expansion of effective networks, which allow exchange of information, knowledge and experience between the different actors involved. Networks play an important role in the diffusion of innovations. They contribute to the generation and propagation of knowledge, to capitalise the experience of early adopters or "first movers" and to increase the interest of potential subsequent adopters of a technology. Networks stimulate compatibility and mutual dependence between actors and help to reduce the risks and fears of adoption. Such networks for cleaner and more efficient supply and end-use energy technologies must be developed at different economic, social and institutional levels and spatial scales. Local, regional and global interactions must be encouraged.

In the remainder of this chapter specific conclusions from the different analyses presented in this document are outlined and some guidelines for further work presented.

9.1 Some results from models with endogenous technological learning

Experience curves have been endogenised in the ERIS and MARKAL models. The ERIS prototype proved beneficial as a tool to test and compare alternative approaches before translating them to more complex energy optimisation models. In ERIS, Non Linear Programming and Mixed Integer Programming formulations were used. The MIP approach was also incorporated into the MARKAL model. Different formulations for the endogenisation of the curves were tested and a number of factors influencing them have been examined, allowing the identification of several aspects that the analyst should take into account when applying the approaches followed here. This experience also showed the difficulties of such endogenous representation, revealing both computational challenges for incorporating it into large-scale energy optimisation models and the necessity of a profound understanding of technology evolution and interactions in order to support the model analyses.

The experience with the two formulations may be summarised as follows:

- Non-linear Program

The original formulation of the problem is a non-linear non-convex optimisation program. With such formulation only local optimal solutions to the problem can be identified when conventional NLP solvers are applied. Those local optima are important for the policy analyst because they show the very different dynamics a system may exhibit and illustrate the risks and opportunities of the “lock-in” process. However, it is also important to devise techniques that allow obtaining global optima. In such respect, as a topic for further research, the application of global optimisation algorithms to the non-convex non-linear problem should be investigated.

The tests with the NLP version already revealed the substantial differences that the presence of the increasing returns mechanism produces in the outcome of the model. As mentioned above, the model introduced new, initially expensive technologies due to cumulative learning effects, producing different solutions than those obtained with the static LP model. Early up-front investments on those technologies allow them to reach competitiveness in the long run. The experiences with the NLP problem drove to the application of MIP techniques in order to guarantee a global optimal solution to the problem.

- Mixed Integer Program

The MIP approach provides a linear approximation of the otherwise non-linear, non-convex mathematical program. Linear segments are used to approximate the cumulative cost curve. Binary variables are applied to define the logical conditions that enforce the segments sequence. The approach is considerably more computational intensive but represents a sensible practical alternative to solve the problem and allows a number of insights.

A number of parameters affects the accuracy of the piece-wise linear representation. Of particular importance are the maximum cumulative capacity, the starting point, the segmentation procedure and the number of segments. They have to be defined carefully

in order to achieve an adequate approximation of the original non-linear learning curve. As a general advice, it is important for the analyst to check the values of specific investment costs and cumulative capacity intervals resulting from a particular combination of these parameters (for a given specification of the progress ratio) for each learning technology and how they affect the relative ranking between the different competing technologies and, if necessary, make the corresponding adjustments.

The maximum cumulative capacity provides an upper bound for the cumulative installations of a given technology and also affects the segmentation. For the same number of segments a lower value may provide a better representation. The partition will be such that the corresponding steps will have higher specific costs, although the intervals of cumulative capacity are smaller. Its effect, however, depends on the segmentation rule applied. Some segmentation patterns are more sensitive than others.

The number of segments influences the precision of the approximation and the solving times. A higher number of segments provides a better representation but the computation time increases as the number of binary variables grows. Thus, its choice is a compromise between the precision required and the computational capability available. The number of segments required can be different depending on the starting point of the learning curve for a given technology. A new technology with high learning potential may need more segments than a mature one, which is already well advanced in its own curve.

An efficient segmentation of the cumulative cost curve must approximate as well as possible the shape of the original curve. Here, a specific procedure with variable length segments was chosen. The rationale for the variable length segmentation comes from the shape of the experience curve itself. The cost reduction is very significant for the first installed units but afterwards the learning effect slows down and saturates. Therefore, a higher estimation error is more likely for the first segments. With shorter segments at the beginning and increasingly longer segments afterwards, it is possible to obtain a better representation for the first region of the curve.

The progress ratio, determining the effectiveness with which the learning process takes place, proved to be one of the most important assumptions of the whole approach. The tests with both NLP and MIP formulations showed the high sensitivity of the model in response to small changes in the assumptions on the progress ratio. Being affected by a number of interacting factors, the progress ratio is highly uncertain. Its future value is difficult to predict, and it is unsure how will it change along the lifetime of the technology. While historical estimates provide valuable information about learning trends, it is not possible to foresee if the observed trends will continue in the future or new developments will cause an alteration of the learning trajectory. A careful technology characterisation and case studies of the main driving factors of change and opportunities for new technologies in specific sectors must support the estimates and assumptions about this parameter.

Besides the progress ratio other influential parameters are the discount rate and the maximum growth rate of the technologies. A high inter-temporal discounting may delay or prevent the introduction of new technologies with initially high investment costs,

even if they have a high learning potential, because technologies with low investment costs will be favoured (even if their O&M costs are high).

The maximum growth rate of the technologies determines to a good extent the possibilities of learning along the time horizon (although other parameters also intervene in shaping such learning potential). If the technology is allowed to grow enough as to be able to reduce its costs to competitive levels, the learning mechanism will be set in motion and the penetration of the technology in the model is likely to occur at its maximum. However, if the allowed growth is not enough (i.e. if opportunities to learn are not sufficient), the technology may remain "locked-out" of the system. Of course, the effect of the maximum growth rate is also linked to the time horizon specified for the model. A longer time horizon allows a higher absolute growth for the different learning technologies and may alter their ranking. The typical "lock-in"/"lock-out" behaviour of the model, although very interesting because it helps to reflect real "lock-in" processes, calls for a careful examination of the assumptions regarding progress ratio, maximum cumulative capacity and maximum penetration rates of a technology.

9.2 Post-Kyoto analysis with ERIS

Using the multi-regional version of ERIS some indicative analyses concerning the future structure of the global electricity generation system under a fast growth demand scenario were performed. Possible effects of Kyoto-like CO₂ emission constraints on the structure of the generation mix and of international emissions trading in the fulfilment of the reduction targets have been outlined, incorporating the effect of endogenous technological learning.

The results of these analyses (and those carried out with MARKAL in other chapters) show that fossil fuels, mainly coal and natural gas, will continue to hold a significant share of the global electricity supply in the next fifty years. Natural gas combined cycle turbines will experience a very dynamic growth, rivalling coal plants as the prevalent generation technology. Nuclear power plants remain a robust option for electricity generation if the path to de-carbonisation is to be followed. However, there are also opportunities for new, emerging technologies. Advanced, more efficient, coal power plants are likely to gain share. Wind turbines constitute a readily cost-competitive alternative in several markets, and could continue growing dynamically. Solar photovoltaics may be brought about in a CO₂ constrained world. Gas fuel cells could also play an important role.

The analysis of Kyoto-like constrained scenarios indicates that a significant departure from carbon intensive generation options is required to fulfil the CO₂ emission targets. Still, even with such constraint global emissions from the electricity system will continue to grow substantially. With an endogenous representation of technology dynamics, early up-front investments are made to stimulate the necessary technological progress of emerging low -or free- carbon generation options, which are then able to play an active role in the mitigation strategy. This early action stimulates technological learning that proves beneficial in terms of both lower costs and emissions in the long run.

Endogenous learning drives to lower estimates of CO₂ abatement costs as compared to a static formulation of technology costs. Also, even in the absence of an emissions constraint, lower long-term emission profiles may appear when, as a result of the endogenous technology dynamics, low-carbon or carbon-free technologies are introduced.

The possibility of trading emission permits, either between Annex I regions or extending the trade to non-Annex I regions, allows some constrained regions to undertake less radical changes in their electricity sectors than what would be required otherwise to fulfil the reduction targets, because they can profit from cheaper mitigation options elsewhere. Thus, trade brings benefits in terms of abatement costs. Nonetheless, under the influence of a global learning mechanism trade does not rule out action in the regions with reduction commitments. Moreover, trade may provide incentives for the penetration of emerging learning technologies in different regions, stimulating accumulation of experience with them, and thus contributing to the progress along their learning curves towards long run cost competitiveness. In particular, international cooperation for emissions abatement between Annex I and non-Annex I countries may drive to significant deployment of new technologies in developing countries, multiplying the opportunities for technological learning as penetration occurs in markets with significant potential and attractive niche markets.

9.3 Stochastic formulation

Due to a number of factors technology developments are uncertain and learning patterns are no exception. The inherent uncertainty of progress ratios as well as other key factors such as demands, emission targets, resource prices etc., affects the outcome and makes sensitivity and/or stochastic analyses necessary. In the case of the learning rates sensitivity analyses in a deterministic framework may be useful to establish a “break-even” value for the progress ratio. That is, the progress ratio at which a given technology may become competitive.

On the other hand, the application of a stochastic programming approach allows handling uncertainty in these key parameters more formally. When the stochastic approach is combined with endogenous learning two basic driving forces of technological change can be examined in a common framework: uncertainty and increasing returns. Here, a traditional two-stage stochastic programming approach, with uncertainty resolution at a fixed point in time, was applied in the ERIS model to account for uncertainties in CO₂ constraints, demand and learning rates.

The results show the importance of taking into account the uncertainty of the technological learning process and also demonstrate the interactions between learning effects and uncertainty in other technical or economical variables. The consideration of uncertain learning rates may drive the model to follow a more prudent and gradual path of investments in learning technologies, thus favouring diversification of investments during the first stage. Uncertainties in other factors, such as emission targets or demands have also an impact, stimulating or delaying technological learning. When uncertainty in emission reduction commitments is considered, the inclusion of the possibility of facing significant constraints drives the model to stimulate early penetration of low-carbon learning technologies. If demand is uncertain, the possibility of a higher demand,

which provides opportunities to grow and accumulate market experience, may also stimulate earlier technological learning. Thus, the results point in the direction of undertaking early action as a preparation for future contingencies.

However, due to the presence of the increasing returns mechanism, the model is very sensitive to the specification of the probabilities of occurrence of the different states of the world and/or to the chosen states-of-the-world themselves. Such response is non-linear and the presence (or weight) of an "optimistic" or a "pessimistic" state of the world may dominate the outcome.

Also, when combined with the MIP approach the computational burden for solving the stochastic model increases considerably. Additional efforts are necessary on the application of more sophisticated and more efficient approaches and algorithms for the stochastic treatment of the learning patterns and other uncertain parameters.

Following the statement of Grübler (1998), who stresses that uncertainty and learning are two core mechanisms of technological change, future work should be devoted to a more thorough exploration of the effects of uncertainty both in learning rates and other factors such as demands and environmental constraints.

An interesting possibility would be exploring the combination of uncertainty in the learning rates with uncertainty in the investment costs that define the starting point of the learning curve. Also, the combination of uncertainties in learning and in CO₂ abatement targets could be pursued in order to examine the interactions between technological change and abatement activities. A hedging strategy against uncertainties in global warming, calling for early abatement efforts will constitute an incentive for new environmentally compatible technologies, which could then begin to move along their learning curves. As they progress to reach competitiveness their accumulated learning will contribute to reduce the costs of the abatement actions (and the associated cost uncertainty). Thus, starting the abatement itself (not necessarily aggressive mitigation actions) would become an important factor to induce the required technological change, which is in its turn necessary to reach the transition at lower economic costs and to clear up the uncertainty associated with such costs (Grubb, 1997, Grübler and Messner, 1998).

9.4 Multi-regional learning in the MARKAL model

Multi-regional technological learning was implemented in the MARKAL model using a mapping procedure that enables the aggregation of regional technologies into a multi-regional learning meta-technology. This allows considering learning spillover between similar technologies across regions and modifying the spatial scope of such spillover process. In such way some effects of the spatial dimension of the technological learning process can be examined. In particular, it is shown that the influence of the scale of learning on the competitiveness of energy technologies in the different regions can be significant and that, as a consequence, the degree of technology spillover has also an important effect on the resulting CO₂ emission profiles.

Also, the importance of the interaction between different scales of learning and different modalities of emissions trading, also a spatial interaction mechanism, and the role of

such interaction on the technology choices in the model, are highlighted. The presence of the learning mechanism and the possibility of learning spillover across regions may stimulate the deployment of low-carbon technologies in different regions, even if they do not face an emission reduction commitment. Such deployment drives to lower emission profiles in those regions, providing an incentive to participate in the trade of permits. Conversely, the allowance of emissions trading tends to de-stimulate the deployment of low-carbon technologies in regions with commitments if cheaper mitigation options are available somewhere else. Still, trade may be an incentive to deploy low-carbon technologies in different regions, particularly if they have potential to become permit sellers. In such way, it could contribute to stimulate their learning processes there, leading to learning spillover toward other regions. The extent of those interactions depends, among other factors, on the "topology" of both learning and trading networks and the evolution of such topologies on time. The manner in which learning and trade are intertwined is, however, complex and deserves more profound examination.

The exercise exemplifies the opportunities that international partnerships may create for the diffusion of emerging technologies. Co-operation among industrialised countries and between these and developing countries in research, development, demonstration and deployment (RD³) may foster the learning process of more efficient and cleaner energy technologies, contributing to boost their competitiveness and accelerating their penetration in the global energy markets (PCAST, 1999). This would allow taking advantage of the positive externalities of innovation and diffusion processes (Grubb et al., 2000) such that long-term environmental and economic benefits can be derived.

In a world with globalised energy markets and global environmental concerns, technological learning partnerships, both at the public and private levels, arise as an important policy intervention mechanism. Learning partnerships could help to share costs and risks of technology development as well as to accelerate both the development and deployment of clean and more efficient energy technologies. As part of the efforts, and in particular as to what concerns developing countries, sound technology transfer (co-operation) strategies must be outlined, with emphasis in building local capabilities and in encouraging active two-way learning and communication processes (Martinot et al., 1997). In this context it is important to notice that, in a globalised world, trade and foreign direct investment are very likely to play an important role as "non-conventional" mechanisms of technology transfer, contributing to build links between industrialised and developing countries promoting learning spillover.

The co-operation may enable some parties (i.e. developing countries) to have access to more environmentally compatible technologies while allowing other parties (i.e. industrialised countries) to make a way into attractive new markets. This could promote "win-win" situations. Industrialised countries may benefit from their competitive advantage as "first movers" and their already growing environmental technologies business sector could increase exports. Developing countries, on the other hand, may profit from the experience of the developed countries to achieve environmental goals at lower costs (Chua, 1999). Stimulation of international learning, however, must be balanced against, and made compatible to, local requirements for a diversified technological choice according to specific needs and development goals and available natural, technological, economic and human resources (Wene, 2000).

A topic of particular interest for further research is the examination of the costs of mitigation of greenhouse gases emissions with and without strategies of co-operative learning, combined with different modalities of geographic-flexibility abatement mechanisms. In order to investigate the effects of such international technological interactions on the evolution of the global energy systems, the refinement of the representation of multi-regional learning in the models is necessary. Thus, the spatial dimension of technological learning and the possibilities of learning "spill-over" are aspects that deserve further investigation.

9.5 Some tests with the two-factor learning curve in the ERIS model

Other factors intervening in the cumulative learning process, such as R&D expenditures, have to be incorporated in order to develop a more comprehensive framework. Besides investments in commercial capacity deployment, R&D constitutes an important channel for knowledge accumulation, particularly relevant at early stages of development of a given technology. In particular, early public R&D expenditures may provide the critical support for technologies with long-term potential, on which private firms are very likely to invest below the necessary levels.

The role of R&D in the learning process of energy technologies is still very poorly understood and considerable work is necessary both in data collection and analysis and in developing an accurate representation of the process in the models. Here, a so-called two-factor learning curve was implemented in the ERIS model. Such formulation allows considering the effects of cumulative R&D expenditures together with those of cumulative capacity in the cost reduction of learning technologies. Some preliminary illustrative results are presented for different specifications of the R&D expenditures per technology. Also, in order to reflect the fact that time lags and depreciation occur in R&D processes, a knowledge stock function is introduced in the place of cumulative R&D expenditures. Such formulation introduces a "forgetting-by-not-doing" feature in the R&D component of the learning process. It is important for the modeller to bear in mind the connotations of such "forgetting-by-not-doing" property. It implies that, leaving aside the effects of accumulating capacity, if no efforts on R&D are made on a given technology its investment costs will increase. However, it still has to be discussed whether this constitutes a realistic representation of the process, and to which extent the forgetting process should be allowed to occur. Also, the possibility of introducing such "forgetting-by-not-doing" characteristic in the cumulative capacity mechanism must be examined carefully.

The introduction of this second factor into the learning curve, besides enabling an improved and more comprehensive (though, of course, not complete or definitive) treatment of the factors involved in the cost reduction, allows the modeller to take into account the effects of R&D in energy technology policy in a more direct way. This constitutes an important first step towards the incorporation of mechanisms to reflect the effects of R&D efforts in the technological progress of energy technologies in the models and in the direction of an endogenous consideration of R&D expenditures such that, being one of the decision variables, their evolution can be affected by other model parameters and, in its turn, influence other model variables.

However, the approach followed here depends critically on obtaining a statistically meaningful estimation of separate learning-by-doing and learning-by-searching indexes. Problems regarding the quality of the underlying data, the procedures for parameter estimation and the formulation itself remain to be solved. Among the difficulties lies the fact that there are mutual interactions between both factors (i.e. they are not independent) and they may be to some extent complementary, rather than substitutes. Therefore, it is complicated to single out their respective contributions.

It is very much necessary to examine more profoundly the influence of the R&D efforts in the learning process of different technologies in order to understand its effects and to conceive meaningful ways for a comprehensive representation of the different knowledge accumulation mechanisms in "bottom-up" models. Also, when assessing the role and effectiveness of both learning mechanisms, it appears sensible to involve the notion of life cycle of the technology into the analysis because their relative importance may change in different stages of evolution of the technology. Such efforts may contribute to provide insights into the effectiveness of R&D in supporting promising energy technologies and could be helpful in advancing the development of more systematic approaches for R&D portfolio analysis.

The task is very relevant from a policy point of view because market experience and public and private R&D constitute interacting pathways that influence the technological trajectory of the energy sector. Therefore, it is necessary to understand how and under which conditions can they operate effectively. The fact that both mechanisms play an important role in setting in motion the learning process drives to the necessity of recognising that both "technology-push" and "demand-pull" aspects are influential in the rate of technical change, although its relative importance could be different for each particular industry and/or technology. Consequently, policy instruments should be conceived taking their particular effects into account.

9.6 Post-Kyoto analysis with a compact global energy system MARKAL model

An indicative post-Kyoto analysis has been performed using a five-region compact "bottom-up" MARKAL model of the global energy system. The response of the model to Kyoto-like CO₂ emission constraints is analysed for a scenario of gradual economic growth and corresponding energy requirements. Emphasis has been given to the contribution that the global electricity generation system may have in a future CO₂-constrained world. Such analysis has been carried out considering endogenous technological learning for several electricity generation technologies.

The discussion has been centred on a Kyoto trend scenario with emission constraints imposed on Annex I regions. The fulfilment of such abatement target under different modalities of emissions trading is examined. As a complement, the response of the system under a Kyoto global trend constraint has been examined. With developing regions assuming CO₂ reduction targets later in the horizon, such scenario provides a stronger decarbonisation of the energy system. The comparison of the deployment of learning technologies under this and the Kyoto-trend scenario allowed identifying interesting aspects of the response of the model in the presence of multi-regional learning spillovers.

The analysis confirms that, as electricity, a clean and flexible final energy carrier, follows a vigorous penetration in diverse end-use sectors and increases its share of the final energy mix, the decarbonisation of the generation system is bound to play an important role in a global CO₂ mitigation strategy. Such decarbonisation process under a Kyoto-like target would offer opportunities for the penetration of less carbon intensive and more efficient emerging generation technologies. Results remain, of course, highly dependent on the assumptions. But, more importantly than the numbers and assumptions here, the dynamics of learning technologies in response to changes in CO₂ constraints, trade modalities and geographical scale of the learning process have been examined.

In particular, it is observed that under the presence of multi-regional learning spillovers in the model, carbon abatement activities that stimulate technological change of low-carbon technologies in a given region may foster their diffusion also in other regions, even in those that do not face an emissions reduction commitment. Such induced technological change may produce positive effects in terms of system costs and emission profiles in those regions. The magnitude of such inducement effect, depends, of course, upon many factors but its presence is an indication of the possible beneficial impacts that "first mover" actions may have on the overall carbon mitigation in the global energy system.

Also, the introduction of multi-regional technological learning spillovers provides a fundamental, though still perfectible, mechanism to represent environmentally induced technological change in the model.

In addition, within the limitations of this "bottom-up" approach, some insights can be gained concerning the costs of compliance of a Kyoto-trend target. The fulfilment of such target, with emission caps imposed on Annex I countries, appears very costly and not particularly effective in achieving a significant long-term diminution of the CO₂ emissions from the global energy system. However, the analysis shows that international co-operation, here represented as emission trading, which increases the where-flexibility of the mitigation, may improve substantially the cost-effectiveness of the abatement actions. In particular, involving developing countries in the trading system may provide access to cheaper mitigation options, helping Annex I countries to reduce their costs of compliance while providing non-Annex I regions an stimulus to decarbonise their own energy systems.

Yet, many issues remain open regarding the implementation of such international collaboration in the climate change context. In particular, although it appears to be sensible bringing developing countries in a strategy for curbing GHG emissions, such undertaking raises a number of implementation issues (e.g. equity, development, technology transfer, monitoring and compliance etc.) that must be addressed, and whose discussion remains outside the scope of this work. However, when examining the issue in the context of the role of technological change in curbing emissions, it becomes evident that a meaningful co-operation requires a sound stimulation of the technological learning of low-carbon technologies if the global energy system is to shift away from the fossil fuel regime in the long run. To be effective, such stimulation must take place at the local, regional and global level both through government and business RD³ partnerships.

Multi-regional interactions are very important for technology diffusion. Interactions between trade of emission permits and learning have also been studied here. The main findings confirm the conclusions obtained previously but some additional insights are gained. The role of emissions trading in stimulating/hindering technological learning appears complex and dependent upon many factors. Different modalities of trade have been examined here. As a rule, the cheaper mitigation options brought about by the trading mechanism tend to produce a disincentive to deploy low-carbon technologies in permit-buying regions. But, on the other hand, trade stimulates their penetration in (potentially) selling ones. The final effects are highly dependent on the configuration of the learning and trading networks, the magnitude of learning spillover between regions and the level of the carbon constraint imposed.

Of course, changes in the spatial configuration of those networks along the time horizon have also noticeable impacts. Here, as an example, a later inclusion of developing regions in the trading system is analysed, in order to determine how such delay affects the "triggering" of the learning mechanism of electricity generation technologies. In this exercise it was observed that delaying the availability of cheaper options in other regions could keep learning processes going on in the constrained regions, which have influence, through spillover effects, on the technology choice of the permit-selling regions as well. By contrast, an earlier global trade may hinder learning processes in constrained regions with expensive mitigation measures but it may foster them in the selling regions. This can drive, provided the existence of learning spillover, to deployment of such low-carbon options also in the constrained (buying) regions. The final outcome depends, among other things, on the relative weight of these counteracting forces.

Nonetheless, the risk still exists that the availability of those initially cheap abatement measures drives to technological choices that "lock" the system into the current fossil trajectory, making difficult the long-term transition towards a different technological regime, necessary for achieving further and more radical mitigation targets (e.g. fuel switching from coal to natural gas power plants could hinder the introduction of other electricity generation options such as renewables). Or, said in another way, that the price signals emitted by the permit trading system may not be sufficiently high to trigger the necessary early technological learning. But, although the evidence presented here is not conclusive, the exercise reveals that trade effects on energy innovation do not necessarily have to be negative. Even in the cases when the trade configuration reduces the incentives to learn, the model still finds cost-effective to stimulate early learning of low-carbon technologies, although the process occurs at a lower scale.

In addition, the influence of the "topology" of the multi-regional learning network on the competitiveness of the learning technologies is examined with some examples. Here only some very specific configurations of learning spillover have been examined, either allowing the different regions to fully benefit from the learning potential in others or completely precluding them to do so. Such changes in the learning configuration, which basically shrink or expand the spatial domain of the learning process, alter the regional ranking of technologies and, consequently, the balance between domestic mitigation measures and transactions (sales/purchases) in the permits market for the different regions, among others. The interaction between different learning and emissions trading

networks appears as an important determinant of the diffusion (or not) of emerging low-carbon technologies in a CO₂-constrained world. The relationships are, however, complex and the effects of learning spillovers should be analysed in more detail. Many other possible combinations of technology spillover linkages across regions could be possible and following this approach their effects can be explored.

In this analysis only the impact of learning in electricity generation technologies has been considered. Further work must be devoted to consider learning in other energy chains and to incorporate interactions within and between technological clusters. This would enable to conduct a more comprehensive evaluation of the effects of technological learning in the global energy system on the costs of GHG mitigation strategies. Of particular importance appears to take into account learning in highly efficient end-use devices, in order to improve the estimation of the potential contribution of energy efficiency to a greenhouse gases mitigation strategy.

9.7 Further work

Concerning technological change in energy systems in general, and the technological learning mechanism in particular, significant work is still required in a number of topics: modelling techniques, solution algorithms, data collection and analysis, case studies, assessment of policy implications, design of policy instruments to make reality the future learning potential of the technologies, etc. An exhaustive presentation of the issues that remain to be addressed is beyond the scope of this work. In this section only some of the topics on energy technology dynamics and modelling that could be the subject of further work are briefly mentioned.

A technology does not evolve alone but in interaction with other technologies, infrastructures, institutions, networks of actors etc. Technological clusters are shaped when related technologies interact and cross-enhance each other, contributing to their mutual development (Nakicenovic, 1997, Grübler, 1998). They play a very important role in technological evolution. Historically, certain clusters have evolved to become dominant, driving to the conformation of technological regimes, which, given among other factors their intertwined and pervasive nature, are difficult to replace. It is very important to study how these interrelated clusters evolve, in order to gain insights into the actions necessary to promote the introduction of clusters of new environmentally sound energy supply and demand technologies. Therefore, it is necessary to develop adequate representations of the mechanisms that account for mutual influences between technologies. One of those mechanisms is technological learning. Technological "proximity" may stimulate a (to some extent) collective learning process. Also, mutual interactions can occur between different clusters.

Some work has been already undertaken to consider energy technology clusters in energy models. The "key technology" concept applied by Seebregts et al. (2000a) allowed taking into account one important aspect of technology interdependence, namely the presence of a key common component whose learning spills over the technologies using it. Also, Gritsevskiy and Nakicenovic (2000) have introduced clusters of technologies, defined according to their technological "proximity", in a single-region global energy systems model, considering learning spill-overs within and between the clusters. Such efforts, however, have been restricted to single-region

models and, as it has been seen here, multi-regional dynamics play a significant role. As a way to consider both clustering effects and multi-regional mechanisms, the "key technology" concept can be combined with the mapping procedure applied here for multi-regional learning, in order to link the learning of multi-regional clusters of technologies. Further attention should be given to the complex interrelations that drive to co-evolution and mutual reinforcement of technologies and other mechanisms acting on the conformation of technological clusters should be incorporated in the models.

Support has to be given to the assumptions applied in the models regarding the behaviour of the different competing technological alternatives. In fact, one of the main bottlenecks for the application of the learning curve methodology to energy technologies has been the lack of reliable data and documented case studies. Although a number of efforts have already begun in order to overcome such shortcomings (e.g. McDonald and Schrattenholzer, 2001), additional activity in this area is required. A careful assessment of the learning potential of emerging energy technologies and documentation of historical behaviour for existing ones is necessary. Cost reductions and/or improvements of performance as well as interactions with other technologies must be examined carefully.

A related aspect is the possibility that the learning curve for one technology be modified along its life cycle (Ayres and Martinàs, 1992, Grübler et al., 1999). Some technologies may experience a slowdown (or acceleration) of the cost reduction process as they move from the early development stage towards commercialisation and, eventually, maturity. When studying historical learning trends it is important to understand the forces underlying those changes. In the models the transitions could be considered by specifying different learning rates for different stages of the technology development. For such purpose threshold values of cumulative capacity could be defined. Below the threshold an initial learning rate will be specified and above the threshold, a second one (higher/lower) can be used. However, if doing so, an important question would be how to choose the capacity values where a technology modifies its learning rate. Given the inherent uncertainty of the learning process it is very difficult to assess the stage at which such changes in the learning process will take place or if they will occur at all for a particular technology. More importantly than the specific aspect of defining capacity thresholds, a more profound study of the dependence of the learning process on the technology life cycle should be carried out. In particular, more empirical evidence must be gathered in order to establish if some stylised facts can be derived.

In connection to this, the definition (or not) of lower limits to the specific cost must be analysed further. Here, a "floor" cost was introduced for some technologies with high learning potential, whose costs would otherwise reach fairly low values under the growth assumptions applied in the model. This, however, implies a cease of the learning process at a given stage of the technology's growth. However, the imposition of limits to the learning of the technologies should be linked either to a study of their cost structure, in order to establish the components whose costs are more likely to be reduced and the magnitude of the corresponding reduction, subjected to expert judgement regarding the expected future costs or linked to life cycle's dependence considerations.

As the definition of learning and other parameters may be difficult, particularly for new technologies, the application of stylised typologies may be useful. According to the type

of manufacturing processes involved in the production of a technology and its position in the life cycle, "typical" parameters supported in empirical findings could be applied. In order to support the development of such stylised topologies, however, the compilation of a substantial number of case studies must be accomplished.

In addition, learning spillovers across regions and/or related technologies appear as a very important issue that should be examined more carefully. It must be noticed that, in the analysis undertaken here, it was assumed that full spillover exists across the different regions that compose a "learning " region. That is, the spill-over coefficients, representing the degree of influence that capacity installed in one region has on the cost reductions of the technology in another region, took an unitary or zero value. But, spillover coefficients will not necessarily be unitary or null and can be affected by a number of factors. Therefore, on one hand, it is important to conduct modelling exercises with different sets of spillover coefficients. On the other hand, work must be devoted to the development of criteria for their choice in the models and conceive methods for their estimation out of empirical data. In connection to this, studies of the "innovation geography" of particular technologies or groups of them must be undertaken. In addition, the spatial and temporal patterns of technological diffusion (e.g. logistic penetration and core/periphery dynamics) must be incorporated. Also, besides considering spillovers in the cumulative capacity mechanism, their presence in the R&D one must also be addressed.

Also, it is relevant to conceive procedures to hard or soft-link the learning-approach with "top-down" energy-economy modelling approaches. Although efforts have been undertaken to endogenise technological change in the so-called "top-down" models, the work has been concentrated in the representation of R&D effects in form of a general knowledge stock, which acts as an additional economic production factor (see, for instance, Buonanno et al., 2000). However, although R&D is very important, particularly in the early stages of development, there is evidence that as technologies advance towards commercialisation, market experience becomes the main instrument for cost reductions. Thus, for the same reason noted above for "bottom-up" models, that is, devising a comprehensive treatment of the knowledge accumulation mechanisms, the inclusion of the market experience and R&D effects in the "top-down" energy-economy framework is necessary. Some work has been already undertaken in this direction. Kypreos (2000), for instance, simulates the learning-by-doing effect in the MERGE3 model, by separating the technology-oriented ETA model, solving it with endogenous learning and providing feedback information to MERGE3 in form of time-dependent costs. Van der Zwaan et al. (1999) and Gerlagh and Van der Zwaan (2000) have developed a macroeconomic model incorporating learning curves for generic carbon and non-carbon energy technologies. However, additional work is necessary in bringing both mechanisms together in a common framework in both "top-down" and "bottom-up" models. Also, it is important to compare the insights provided by both types of models and to understand the possible discrepancies between them.

Finally, although challenging, it is very important to advance in the endogenisation of technological change in energy systems models. The treatment given to technology dynamics in those decision-support tools affects our understanding of a number of issues concerning the evolution of energy systems and their long-term environmental, economic and social impacts. The comprehension of the continuous technological

substitution processes, where some technologies (or clusters of technologies) develop and reach a dominant position, while other are "locked-out", must be improved. The role of the pervasive technological uncertainty must be outlined more clearly. The driving forces behind the learning curve better understood. Also, among other issues, the effects of the emergence and decay of technological regimes on the costs and timing of strategies to mitigate environmental impacts of the energy systems must be investigated. An adequate framework is necessary to gain insights about the underlying forces that drive this evolution and their interaction and to provide guidelines regarding the actions required to move towards the long-term sustainability of the system.

List of Abbreviations

CO ₂	Carbon Dioxide
CPLEX	Solver of LP and MIP problems
DOE	U.S. Department of Energy
EC	European Commission
ECN	The Netherlands Energy Research Foundation
EFOM	Energy Supply Model of the EC-Modelling System
ERIS	<u>E</u> nergy <u>R</u> esearch and <u>I</u> ncvestment <u>S</u> trategy model
ETA	<u>E</u> nergy <u>T</u> echnology <u>A</u> ssessment. A simplified technology oriented model, part of the MERGE model.
ETSAP	Energy Technology Systems Analysis Programme (ETSAP) of the IEA
GENIE	<u>G</u> lobal <u>E</u> nergy System with <u>I</u> nternalized <u>E</u> xperience Curves Model
GHG	Greenhouse Gases
IEA	International Energy Agency of the OECD
IEPE	Institut d'Économie et de Politique de l'Énergie- CNRS
IER	Institut für Energiewirtschaft und Rationelle Energieanwendung
IIASA	International Institute for Applied Systems Analysis
LP	Linear Programming
MARKAL	<u>M</u> arket <u>A</u> llocation model
MERGE3	<u>M</u> odel for <u>E</u> valuating <u>R</u> egional and <u>G</u> lobal <u>E</u> ffects of GHG Policies
MESSAGE	Energy optimisation model developed at IIASA
MINOS5	Solver for LP and NLP problems
MIP	Mixed Integer Programming
NEMS	<u>N</u> ational <u>E</u> nergy <u>M</u> odelling <u>S</u> ystem of the DOE
NLP	Non Linear Programming
NTUA	National Technical University of Athens
POLES	<u>P</u> rospective <u>O</u> utlook on <u>L</u> ong-term <u>E</u> nergy <u>S</u> ystems Model
PSI	Paul Scherrer Institute
R&D	Research and Development
RD ³	Research, Development, Demonstration and Deployment
RICE	<u>R</u> egional <u>I</u> ntegrated Model of <u>C</u> limate Change and the <u>E</u> conomy
SAPIENT	<u>S</u> ystems <u>A</u> nalysis for <u>P</u> rogress and <u>I</u> nnovation in <u>E</u> nergy <u>T</u> echnologies- European Commission Project
TEEM	Energy <u>T</u> echnology Dynamics and Advanced <u>E</u> nergy System <u>M</u> odelling Project
UNFCCC	United Nations Framework Convention on Climate Change
WEC	World Energy Council

Appendix 1. The RMARKAL MIP code

This section presents the implementation of the MIP approach to endogenise experience curves in the RMARKAL model carried out here. This implementation corresponds to the formulation described in numeral 3.7. The SETS, PARAMETERS, VARIABLES, and EQUATIONS that must be added to the normal RMARKAL code are described. For simplicity, only the single-region model code is shown.

Before presenting the MIP code a brief description of the "bottom-up" energy systems optimisation MARKAL model is provided. The description is adopted from Berger et al. (1992). Additional information can be found also in Fishbone et al. (1983), Fishbone and Abilock (1981) and Berger et al. (1987), among others.

MARKAL, which stands for MARKet ALlocation model, is a dynamic multi-period process-oriented linear programming model of the energy system of a country or region. It was developed as a co-operative effort within the Energy Systems Technology Analysis Programme (ETSAP) of the International Energy Agency (IEA). Along its history it has undergone a series of incremental improvements and has been widely applied (e.g. Kram, 1993). The MARKAL family of models comprises, among others, the standard MARKAL with inelastic demands, MARKAL-ED with elastic demands (Loulou and Lavigne, 1996), MARKAL-MACRO (Hamilton et al., 1992) and MARKAL-MICRO. The multi-regional RMARKAL model allows coupling several energy systems considering trade of energy carriers and emissions (Decisionware, 1997). A stochastic single-region version that implements a two-stage programming approach is also available. Recently, the TIMES model (The Integrated MARKAL-EFOM System) has been released (ETSAP Newsletters, January 2000). Such model, which builds upon the MARKAL and EFOM models, adding new features and flexibilities, is currently undergoing the test phase.

MARKAL allows a detailed representation of the technologies and energy carriers involved in the different energy chains from resource extraction, conversion, transmission and distribution to end-uses. Technical and economic characteristics of current and (future) candidate technologies belonging to the different energy chains are specified and their interconnections are defined through the so-called Reference Energy System (RES).

The basic variables in the model are activities, capacities, investments and resources (mining, imports, exports, renewables etc.).

Some of the data customarily required for a given technology are: Investment costs, fixed O&M costs, variable O&M costs, efficiency, availability factors, lifetime, starting year, upper and lower capacity and/or activity bounds, maximum and/or minimum capacity growth rates, polluting emission coefficients, residual historical capacity (where applicable), etc.

Typical constraints in the model are flow balances, capacity transfer, demand constraints, production relations, peaking and base-load requirements for electricity and district heating technologies, accounting of environmental emissions, environmental

constraints, exogenous activity and capacity bounds, minimum and maximum market penetration constraints etc. (Berger et al., 1992). Additional user-defined constraints can also be formulated.

It is a demand-driven model. That is, demands are exogenously specified. The standard solution corresponds to the least-cost energy system that satisfies those exogenously given demands. Other objective functions can also be chosen. A typical application of the model is the assessment of energy technologies under different scenarios, e.g. examining the technology mix necessary for the system to meet a given environmental constraint.

A1.1 Model SETS

TEG	Endogenous learning technologies
KP	Index of segments
RP	Index of segments - alias

TEG and RP are declared in MMSETS1.INC. KP has to be declared in the *.gen file before calling MMINIT1.INC.

The elements of KP are dictated by the maximum number of segments given for one technology. That is, if there are two technologies with experience curves, one of them with 4 segments and the other with 6 segments, then the set KP will be /0*6/.

A1.2 Model PARAMETERS

Declared and defined in MMCOEF1.INC

SC0(TEG)	Initial specific cost
PRAT(TEG)	Progress ratio
PBT(TEG)	Learning curve parameter b (computed from PRAT(TEG))
PAT(TEG)	Learning curve parameter a (computed from SC0 and PBT)
CCAP0(TEG)	Initial cumulative capacity
CCOST0(TEG)	Initial cumulative cost
CCAPM(TEG)	Maximum cumulative capacity
CCOSTM(TEG)	Maximum cumulative cost
CCAPK(KP, TEG)	Kink points for cumulative capacity
CCOSTK (KP, TEG)	Kink points for cumulative cost
BETA(KP, TEG)	Beta parameter for cumulative cost interpolation
ALPH(KP, TEG)	Alpha parameter for cumulative cost interpolation
SEG(TEG)	Number of segments per technology
WEIG(KP, TEG)	Weighting factors for the segmentation

A1.3 Model VARIABLES

Declared in MMVARS1.INC

CCAP(TP, TEG)	Cumulative capacity
LAMBD(TP, TEG, KP)	Lambda variables for capacity interpolation

DELTA (TP, TEG, KP)	Delta binary variables
CCOST(TP, TEG)	Cumulative cost
IC(TC, TEG)	Undiscounted investments
SV_INV(TP, TEG)	Salvage on learning investments

A1.4 Model EQUATIONS

Defined in MMEQTEG1.INC, listed in MMEQUA1.INC and MODEL1.MRK

EQ_CUINV(TP, TEG)	Definition of cumulative capacity
EQ_CC(TP, TEG)	Interpolation of cumulative capacity
EQ_DEL(TP, TEG)	Sum of delta variables to 1
EQ_COS(TP, TEG)	Cumulative cost interpolation
EQ_LA1(TP, TEG, KP)	Logical conditions using delta variables 1
EQ_LA2(TP, TEG, KP)	Logical conditions using delta variables 2
EQ_EXPE1(TP, TEG, KP)	Experience grows-Additional constraint 1
EQ_EXPE2(TP, TEG, KP)	Experience grows-Additional constraint 2
EQ_IC1(TB, TEG)	Undiscounted investments for the first period
EQ_IC2(TP, TEG)	Undiscounted investments for other periods
EQ_SV(TP, TEG)	Salvage on learning investments
EQ_SV2(TP, TEG)	Additional condition for salvage

A new additional file is used for the main formulation of the MIP approach. The other changes are done on existing (renamed) files.

1. File MMEQTEG1.INC

```

=====
*LB* MMEQTEG1.INC technological change equations - Formulation 1 (N. Mattsson)
* %1 - equation name prefix 'EQ' or 'MS' or 'MR'
* %2 - SOW indicator => " or 'SOW,' or "
* %3 - coef qualifier => " or " or '_R'
* %4 - variable/coef prefix => " or 'S_' or "
* %5 - REGIONal indicator => " or " or 'REG,'
* %6 - regional scaling => " or " or '(REG)'
* %7 - loop control set => 'TPCON(TP,CON)' or 'TPNCON(TP,SOW,CON)' or *
'TPCON_R(REG,TP,CON)'
*GG* V3.0 modularise calls to equations
=====
*$ONLISTING
* Cumulative capacity definition

%1_CUINV(%5TP, %5TEG)$ (ORD(TP) GE TCH_STRT%3(%5TEG)).CCAP(%5TP, %5TEG) =E=
SUM(TC$((ORD(TC) LE ORD(TP))$ (ORD(TC) GE TCH_STRT%3(%5TEG))), INV(TC,
%5TEG))+CCAP0(TEG);

* Cumulative Capacity Interpolation

%1_CC(%5TP, %5TEG)$ (ORD(TP) GE TCH_STRT%3(%5TEG)).CCAP(%5TP, %5TEG) =E=
SUM(KP$((ORD(KP) GE 2)$ (ORD(KP) LE SEG(TEG)+1)), LAMBD(%5TP, %5TEG, KP));

* Force sum of binary variables delta to 1

```

$\%1_DEL(\%5TP, \%5TEG)\$(ORD(TP) \text{ GE } TCH_STRT\%3(\%5TEG))..SUM(KP\$(ORD(KP) \text{ GE } 2)\$(ORD(KP) \text{ LE } SEG(TEG)+1)), DELTA(\%5TP, \%5TEG, KP)) =E= 1;$

* Cumulative Cost Interpolation

$\%1_COS(\%5TP, \%5TEG)\$(ORD(TP) \text{ GE } TCH_STRT\%3(\%5TEG))..CCOST(\%5TP, \%5TEG)=E=SUM(KP\$(ORD(KP) \text{ GE } 2)\$(ORD(KP) \text{ LE } SEG(TEG)+1)), LAMBDA(\%5TP, \%5TEG, KP)*BETA(KP, \%5TEG)+DELTA(\%5TP, \%5TEG, KP)*ALPHA(KP, \%5TEG));$

* Constraints on lambda

$\%1_LA1(\%5TP, \%5TEG, KP)\$(ORD(KP) \text{ GE } 2)\$(ORD(KP) \text{ LE } SEG(TEG)+1))\$(ORD(TP) \text{ GE } TCH_STRT\%3(\%5TEG))..LAMBDA(\%5TP, \%5TEG, KP)=G=CCAPK(KP-1, TEG)*DELTA(\%5TP, \%5TEG, KP);$

$\%1_LA2(\%5TP, \%5TEG, KP)\$(ORD(KP) \text{ GE } 2)\$(ORD(KP) \text{ LE } SEG(TEG)+1))\$(ORD(TP) \text{ GE } TCH_STRT\%3(\%5TEG))..LAMBDA(\%5TP, \%5TEG, KP)=L=CCAPK(KP, TEG)*DELTA(\%5TP, \%5TEG, KP);$

* Additional constraints to improve solution time

$\%1_EXPE1(\%5TP, \%5TEG, KP)\$(ORD(KP) \text{ GE } 2)\$(ORD(KP) \text{ LE } SEG(TEG)+1))\$(ORD(TP) \text{ GE } TCH_STRT\%3(\%5TEG))..SUM(RP\$(ORD(RP) \text{ LE } ORD(KP)\$(ORD(RP) \text{ GE } 2)), DELTA(\%5TP, \%5TEG, RP)) =G= SUM(RP\$(ORD(RP) \text{ LE } ORD(KP)\$(ORD(RP) \text{ GE } 2)), DELTA(\%5TP+1, \%5TEG, RP));$

$\%1_EXPE2(\%5TP, \%5TEG, KP)\$(ORD(KP) \text{ GE } 2) \text{ AND } (NOT \text{ TLAST}(TP))\$(ORD(KP) \text{ LE } SEG(TEG)+1))\$(ORD(TP) \text{ GE } TCH_STRT\%3(\%5TEG))..SUM(RP\$(ORD(RP) \text{ GE } ORD(KP)), DELTA(\%5TP, \%5TEG, RP)) =L= SUM(RP\$(ORD(RP) \text{ GE } ORD(KP)), DELTA(\%5TP+1, \%5TEG, RP));$

* Investments to be discounted 1st period the technology is available

$\%1_IC1(\%5TP, \%5TEG)\$(ORD(TP) \text{ EQ } TCH_STRT\%3(\%5TEG))..IC(TP, TEG) =E= CCOST(TP, TEG) - CCOST0(TEG);$

* Investments to be discounted , other periods

$\%1_IC2(\%5TP, \%5TEG)\$(ORD(TP) \text{ GT } TCH_STRT\%3(\%5TEG))..IC(TP, TEG) =E= CCOST(TP, TEG) - CCOST(TP-1, TEG);$

* Salvage of learning investments

$\%1_SV(\%5TP, \%5TEG)\$(ORD(TP) + TCH_LIFE(TEG) - CARD(TP)-1) \text{ GT } 0)..SV_INV(TP, TEG) =E= (IC(TP, TEG)$

GG V1.5m handle sunk/released material

+
 $SUM(ENC \$ SNK_ENC(ENC,TEG),$
 $SAL_SNK(ENC,TP)$
 $* (PRC_INP1(TEG,ENC) + CON_INP1(TEG,ENC) + DMD_MATID(TEG,ENC))$
 $* (1\$(NOT \text{ ENU}(ENC)) + ((1+DISCOUNT)**NYRSPER)\$ENU(ENC)))$

+
 $SUM(ENC \$ (REL_ENC(ENC,TEG) \text{ AND } ((ORD(TP) + TCH_LIFE(TEG) - CARD(TP)) \text{ GT } 0)),$
 $SAL_REL(ENC)$
 $* (PRC_OUT1(TEG,ENC) + CON_OUT1(TEG,ENC) + DMD_MOTID(TEG,ENC))$
 $* ((1+DISCOUNT)** (-NYRSPER * (TCH_LIFE(TEG) + 1)\$ENU(ENC))))$

* correct salvage credit for technology-based discount rates

$* (1 - (1 + DISCOUNT\$(NOT \text{ TCH_DISC}(TEG)) + TCH_DISC(TEG))$
 $** (- NYRSPER * (ORD(TP) + TCH_LIFE(TEG) - CARD(TP) - 1)))$

```

/ ((1 + DISCOUNT$(NOT TCH_DISC(TEG)) + TCH_DISC(TEG))
** (NYRSPER * (CARD(TP) + 1 - ORD(TP))))
/ (1 - (1 + DISCOUNT$(NOT TCH_DISC(TEG)) + TCH_DISC(TEG))
** (- NYRSPER * TCH_LIFE(TEG)))
);

```

```

%1_SV2(%5TP, %5TEG)$((ORD(TP) + TCH_LIFE(TEG) - CARD(TP)-1) LE 0)..SV_INV(TP, TEG)
=E= 0;

```

```

*$OFFLISTING

```

2. File MMCOEF1.INC

```

*****
*
* Parameters technological change
*
*****

```

```

PARAMETER PAT(TEG) / EMPTY 0 /;
PARAMETER SC0(TEG) / EMPTY 0 /;
PARAMETER PBT(TEG) / EMPTY 0 /;
PARAMETER PRAT(TEG) / EMPTY 0 /;
PARAMETER SEG(TEG) / EMPTY 0 /;
PARAMETER CCAP0(TEG) / EMPTY 0 /;
PARAMETER CCOST0(TEG) / EMPTY 0 /;
PARAMETER CCOSTM(TEG) / EMPTY 0 /;
PARAMETER CCAPM(TEG) / EMPTY 0 /;
PARAMETER WEIG(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER CCOSTK(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER CCAPK(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER BETA(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER ALPH(KP, TEG) / EMPTY.EMPTY 0 /;

```

```

* computation of the learning curve exponent

```

```

PBT(TEG)=-LOG(PRAT(TEG))/LOG(2);

```

```

* computation of the learning curve coefficient

```

```

PAT(TEG)=SC0(TEG)*(CCAP0(TEG)**(PBT(TEG)));

```

```

* assignment of the initial cumulative cost

```

```

CCOST0(TEG)=(PAT(TEG)/(1-PBT(TEG)))*(CCAP0(TEG)**(1-PBT(TEG)));

```

```

* assignment of the maximum cumulative cost

```

```

CCOSTM(TEG)=(PAT(TEG)/(1-PBT(TEG)))*(CCAPM(TEG)**(1-PBT(TEG)));

```

```

* assignment of the kink points for cumulative cost

```

```

ICOUNT=1;
LOOP(KP$(ORD(KP) GE 2),
WEIG(KP, TEG)=(2**(-SEG(TEG)+ICOUNT-1))/(sum(RP$(ORD(RP) LE (SEG(TEG)), (2**(-
SEG(TEG)+ORD(RP)-1)))));
ICOUNT= ICOUNT+1;
);

```

```

CCOSTK('0', TEG)=CCOST0(TEG);

```

```

ICOUNT=1;
LOOP(KP$(ORD(KP) GE 2),
CCOSTK(KP, TEG)=CCOSTK(KP-1, TEG)+((CCOSTM(TEG)-CCOST0(TEG))*WEIG(KP, TEG));
ICOUNT= ICOUNT+1;
);

```

* assignment of the kink points for cumulative capacity

```

CCAPK(KP, TEG)$ (ORD(KP) LE SEG(TEG)+1)=(((1-PBT(TEG))/PAT(TEG))*CCOSTK(KP,
TEG))* (1/(1-PBT(TEG)));

```

* assignment of beta coeff. for interpolation of cumulative cost

```

BETA(KP, TEG)$ (ORD(KP) LE SEG(TEG)+1)= (CCOSTK(KP, TEG)-CCOSTK(KP-1,
TEG))/(CCAPK(KP, TEG)-CCAPK(KP-1, TEG));

```

* assignment of alpha coeff. for interpolation of cumulative cost

```

ALPH(KP, TEG)$ (ORD(KP) LE SEG(TEG)+1)=CCOSTK(KP-1, TEG) - BETA(KP,
TEG)*CCAPK(KP-1, TEG);

```

* Set the investment cost of the learning technologies to zero

```

TCH_INVCOS(TEG, TP)=0;

```

3. File MMVARS1.INC

```

*=====
* Technological change variables *
*=====

```

POSITIVE VARIABLES

```

LAMBDA(TP, TEG, KP)
CCAP(TP, TEG)
CCOST(TP, TEG)
IC(TP, TEG)
SV_INV(TP, TEG)

```

BINARY VARIABLES

```

DELTA(TP, TEG, KP)

```

4. File MMEQPRI1.INC

* Technological change - Capacity for learning technologies

```

SUM(TP%8TCH%3(%5TP, %9%2TEG),

```

```

(
(1 / ((1 + DISCOUNT) ** (- STARTYRS + NYRSPER * (ORD(TP) - 1)))) *

```

* add fractional lifetime correction multiplier

```

CRF_RAT(TEG) * FRACLIFE(TEG) *
(IC(%5TP, %5TEG) - SV_INV(%5TP, %5TEG)))

```

```

)+

```

5. File MMEQUA1.INC

5.1 Include the following lines into the EQUATIONS declaration:

* MIP formulation of learning curves

EQ_CUINV(TP, TEG)	Cumulative Capacity Definition
EQ_CC(TP, TEG)	Cumulative Capacity Interpolation
EQ_DEL(TP, TEG)	Delta to 1
EQ_COS(TP, TEG)	Cumulative Cost
EQ_LA1(TP, TEG, KP)	Logical Conditions 1
EQ_LA2(TP, TEG, KP)	Logical Conditions 2
EQ_EXPE1(TP, TEG, KP)	Experience grows 1
EQ_EXPE2(TP, TEG, KP)	Experience grows 2
EQ_IC1(TP, TEG)	Investments tech. change starting period
EQ_IC2(TP, TEG)	Investments tech. change other periods
EQ_SV(TP, TEG)	Salvage on investments
EQ_SV2(TP, TEG)	Additional condition for salvage

5.2 Make the following change to call the file with the modified objective function:

```
*=====*
```

```
* Total Discounted System Cost *
```

```
*=====*
```

```
$BATINCLUDE MMEQPRI1.INC EQ " " " " " " " " " " 'E'
```

5.3 Call the file with the technological change equations:

```
*=====*
```

```
* Technological change equations *
```

```
* *
```

```
*=====*
```

```
$BATINCLUDE MMEQTEG1.INC EQ " " " " " " " "
```

6. File MODEL1.MRK

Include the following list of equations into the MODEL declaration

```
* Technological Change
EQ_CUINV
EQ_CC
EQ_DEL
EQ_COS
EQ_LA1
EQ_LA2
EQ_IC1
EQ_IC2
EQ_EXPE1
EQ_EXPE2
EQ_SV
EQ_SV2
```

7. File MMINIT1.INC

```
*Technological change
SET TEG(TCH) / EMPTY /;
```

8. File MMSETS1.INC

* Set of learning technologies

SETS TPTEG;

TPTEG(TP,TEG) = TPTCH(TP,TEG);

Declare an Alias of set KP

ALIAS(KP, RP);

9. File SOLVE1.MRK

* main solve for MARKAL

\$IF NOT '%RUN_MREG%' == 'YES' SOLVE MRK MINIMIZING OBJZ USING MIP;

10. File MMINCLU1.INC

Change the names of included files where required to use the new formulation:

```
$ INCLUDE MMSETS1.INC
$ INCLUDE MMCOEF1.INC
$ INCLUDE MMVARS1.INC
$ INCLUDE MMEQUA1.INC
$ INCLUDE MODEL1.MRK
```

* solve MRK if MARKAL or MM with PRESOLVE run

```
$ IF %3 == 'PRESOLVE' $ BATINCLUDE SOLVE1.MRK %3
  IF (MODE = 1,
$   BATINCLUDE SOLVE1.MRK %3
  );
```

11. File XXXXX.GEN

Include the following in the *.gen file

OPTION MIP=CPLEX; or OSL

Declare and define set KP (KP is an ordered set and has to be declared at the very beginning, that is, even before calling MMINIT1.INC)

SET KP / 0*6 /;

```
$ INCLUDE MMINIT1.INC
$BATINCLUDE MMINCLU1.INC GMARKAL START SOLVE
```

12. File XXXXX.DD

SETS

```
SET TEG(TCH) 'ENDOGENOUS TECH. CHANGE'
/
E61 'WIND TURBINE'
E41 'SOLAR PHOTOVOLTAICS'
/
```

PARAMETERS

SEG(TCH) number of segments per technology

/ E61 6
E41 5 /

SC0(TCH)

/ E61 800.
E41 5000. /

PRAT(TCH)

/ E61 0.85
E41 0.85 /

CCAP0(TCH)

/ E61 5.0
E41 0.5 /

CCAPM(TCH)

/ E61 3000.
E41 3000 /

Appendix 2. Description of ERIS

The description of ERIS presented here has been adopted from Kypreos et al. (2000). ERIS represents the global electricity market supplied by a number of electricity generation technologies. The linear model underlying the prototype was formulated on the basis of a small MESSAGE⁹⁸ model. A simplification is made concerning interpolation of values between periods: the activity over a period is assumed to be constant, i.e. a step function is used instead of linear interpolation of the values. All variables in the linear model refer to average annual values in the period. The time horizon used for the analysis here is 1990 to 2050 with 10-year time steps (including the 10 years after 2050).

The linear model is completely static, i.e. all parameters are constant over time⁹⁹. The non-linear and MIP models have reduction factors for the investment costs as a function of the cumulative installations. Regionalised constraints on demand-supply balance, fuel consumption and fuel production, capacity definition, maximum and minimum capacity growth, peaking constraints, regional and global (annual and cumulative) emissions of pollutants, maximum annual potential for renewables, maximum cumulative potential for fossil fuels and balance of traded goods are defined.

A2.1 Model parameters

In the current version of the model, some parameters have been made region, time or state-of-the-world dependent. Where required, this is indicated with the corresponding index but, for the sake of simplicity, the stochastic index has been omitted.

A2.1.1 Indexes

t	Time index
te	Technology index
pl	Pollutant index
fu	Fuel index
pk	Technologies contributing to the peak
rg	Region
trd	Traded goods (energy carriers or emission permits)
ns	State of the world (stochastic formulation)

A2.1.2 Parameters

Δ_t	Length of the time period (years)
d	Discount rate (fraction)
$\eta_{T\&D}$	Transmission&Distribution efficiency (fraction)
pf	Augmentation factor for peak demand (fraction)

⁹⁸ MESSAGE is the energy optimisation model developed at IIASA (Messner and Strubegger, 1995)

⁹⁹ However, the model is formulated in a general way and with very small changes it can be specified as a dynamic linear program and the time horizon extended. Also, an endogenous specification of other parameters such as O&M costs or efficiency could be incorporated in the future.

frac	Fraction of load to be met by Gas Turbines (fraction)
$D_{t,rg}$	Demand for electricity in period t and region rg (secondary energy)
η_{rg}^{te}	Conversion efficiency of a given technology te in the region rg(fraction)
$c_{t,rg}^{te}$	Capacity of technology te built before 1990 and still available in period t (GW)
π_{rg}^{te}	Plant factor of the technology te in the region rg(fraction)
i_{rg}^{te}	Specific investment cost of the technology in period t (\$/kW)
f_{rg}^{te}	Fixed O&M cost of the technology in period t (\$/kW/year)
v_{rg}^{te}	Variable O&M cost of the technology in period t (\$/kWyr)
l^{te}	Lifetime of technology te (periods)
s_t^{te}	Salvage factor for terminal correction
$r_{t,rg}^{fu}$	Resource cost (\$/kWyr)
e_{fu}^{pl}	Specific emissions of pollutant pl per unit of fuel consumed (ton C/kWyr)
EA_t^{pl}	Global maximum annual emissions of pollutant pl (Mton C)
ET^{pl}	Global maximum cumulative emissions of pollutant pl (Mton C)
$IER_{t,rg}^{pl}$	Regional initial endowments of emissions rights of pollutant pl (Mton C)
γ_{rg}^{te}	Maximum growth rate per period for the technology te in region rg (fraction)
g_{rg}^{te}	RHS of market penetration constraint for the technology te in region rg (GW)
α_{rg}^{te}	Minimum growth rate per period for the technology te in region rg (fraction)
AP_{rg}^{arm}	Maximum annual renewable activity per region rg (GWyr/yr)
RA_{rg}^{fu}	Cumulative resource availability per region rg (GWyr)

The salvage cost for terminal correction s_{te}^t is explicitly formulated as:

$$s_t^{te} = \frac{\left(1 - (1+d)^{-\Delta_t * (ord(t) + l^{te} - card(t) - 1)}\right)}{\frac{(1+d)^{\Delta_t * (card(t) + 1 - ord(t))}}{(1 - (1+d)^{-\Delta_t * l^{te}}}}} \quad (47)$$

With: $ord(t) + l^{te} - card(t) - 1 > 0$.

Some additional parameters are required in the non-linear and MIP models to define the learning curve in terms of the progress ratio and the initial cumulative capacity for which the initial costs (i.e., the constant costs of the linear model) are valid:

$dcap^{te}$	Global cumulative capacity to which the initial costs refer (GW)
b^{te}	Learning by doing parameter
$2^{-b^{te}}$	Progress ratio of a learning technology

A2.1.3 Model variables

$A_{t,rg}^{te}$	Annual activity (electricity generation) of a technology te for the period t and region rg (GWyr)
$I_{t,rg}^{te}$	Annual new capacity of a given technology in period t-1 in region rg (GW)
$C_{t,rg}^{te}$	Installed capacity of a given technology in period t in the region rg (GW)
$R_{t,rg}^{fu}$	Annual consumption of fuel in period t in the region rg (GWyr)

$PN_{t,rg}^{fu}$ Annual production of fuel in period t in the region rg (GWyr)

Additional variable for the nonlinear and MIP learning models:

G_t^{te} Global growth factor - relative to $dcap^{te}$ - for a given technology up to period t

Additional variable for the MIP model:

$ICOST_t^{te}$ Global investment costs for a learning technology in the period t

Additional variable for the multi-regional model with trade:

$NTX_{t,rg}^{trd}$ Net amount of traded good per region (GWyr or Mt C)

A2.2 Model constraints

This section presents the formulation of the constraints used in the model.

A2.2.1 Demand-Supply Balance

The production of the technologies must meet the demand in each time period t and region rg.

$$\sum_{te} A_{t,rg}^{te} \geq \frac{D_{t,rg}}{\eta_{T\&D}} \quad (48)$$

A2.2.2 Annual fuel consumption

The annual consumption of fuel by the corresponding technologies is given as:

$$R_{t,rg}^{fu} \geq \sum_{tetofu} \frac{A_{t,rg}^{te}}{\eta_{rg}^{te}} \quad (49)$$

tetofu: Mapping set for technologies te consuming the given fuel fu

A2.2.3 Balance of annual fuel production per region

The annual fuel production in a given region rg must be greater than the fuel consumption plus the traded amount

$$PN_{t,rg}^{fu} \geq R_{t,rg}^{fu} + NTX_{t,rg}^{fu} \quad (50)$$

A2.2.4 Definition of installed capacity

The installed capacity of a technology te in time t is defined as the capacity still existing in the period t from pre-1990 installations plus new installations still existing up to the beginning of the period

$$C_{t,rg}^{te} = c_{t,rg}^{te} + \sum_{\tau=\max(t-l^{te}+1, 1)}^t I_{\tau,rg}^{te} * \Delta_t \quad (51)$$

A2.2.5 Annual capacity constraint

The production of a technology affected by the corresponding plant factor cannot be larger than its installed capacity

$$\frac{A_{t,rg}^{te}}{\pi_{rg}^{te}} \leq C_{t,rg}^{te} \quad (52)$$

A2.2.6 Upper dynamic constraint on capacity

This constraint limits the build-up rates of new technologies. Installed capacity in a period is limited relative to the installed capacity in the previous period affected by a growth parameter (γ_{rg}^{te}) plus the so-called start-up parameter (g_{rg}^{te})

$$C_{t,rg}^{te} \leq \gamma_{rg}^{te} C_{t-1,rg}^{te} + g_{rg}^{te} \quad (53)$$

A2.2.7 Lower dynamic constraint on capacity

This constraint limits the phase-out rates of existing technologies. Installed capacity in a period must be at least a fraction of the installed capacity in the previous period. The fraction is defined by the minimum growth rate per period (α_{rg}^{te}).

$$C_{t,rg}^{te} \geq \alpha_{rg}^{te} C_{t-1,rg}^{te} \quad (54)$$

A2.2.8 Regional annual emissions of pollutant pl

Annual emissions of a given pollutant in a region rg are computed from the fuel consumption and the corresponding amount of traded emission permits (if trade allowed):

$$IER_{t,rg}^{pl} \geq \sum_{futo_{pl}} R_{t,rg}^{fu} * e_{pl}^{fu} + NTX_{t,rg}^{pl} \quad (55)$$

futo_{pl}: Mapping set of fuels fu to the corresponding pollutant pl

The equation above defines the initial endowments of regional emission rights.

A2.2.9 Global annual emissions of pollutant pl

Global emissions of a given pollutant are computed from the fuel consumption and added up across regions

$$EA_t^{pl} \geq \sum_{rg} \sum_{futo_{pl}} R_{t,rg}^{fu} * e_{pl}^{fu} \quad (56)$$

A2.2.10 Cumulative emissions of pollutant pl

Cumulative emissions are computed based on step-wise interpolation, and added up across time and regions:

$$ET^{pl} \geq \sum_{t=1}^T \sum_{rg} \sum_{futo pl} R_{t,rg}^{fu} * e_{pl}^{fu} * \Delta_t \quad (57)$$

A2.2.11 Cumulative capacity

In the nonlinear and MIP models with learning, an additional constraint determines the global cumulative installations (right-hand side of the following equation) and the global growth relative to the initial cumulative capacity.

$$G_t^{te} * dcap^{te} = dcap^{te} + \sum_{rg} \sum_{\tau=1}^t I_{\tau,rg}^{te} * \Delta_{\tau} \quad (58)$$

A2.2.12 Peaking constraint

This constraint ensures that extra-capacity is installed to meet peak demand

$$\sum_{pk} C_{t,rg}^{te} \geq D_{t,rg} * \frac{pf}{\eta_{T\&D}} \quad (59)$$

pk: Set containing technologies contributing to the peak

A2.2.13 Optional peaking constraint

A specific peaking technology (e.g. gas turbine) must produce a given load fraction:

$$C_{t,rg}^{te} \geq D_{t,rg} * \frac{frac}{\eta_{T\&D}} \quad (60)$$

A2.2.14 Maximum annual potential for renewable technologies

This constraint limits the annual activity of renewable technologies

$$A_{t,rg}^{arn} \leq AP_{rg}^{arn} \quad (61)$$

arn: Set of technologies with maximum annual production potential

A2.2.15 Maximum cumulative potential for fossil fuels

This constraint limits the cumulative availability of resources for the whole time horizon:

$$RA_{fu,rg} \geq \sum_{t=1}^T PN_{t,rg}^{fu} \quad (62)$$

Although the two constraints above have been described here for renewable and non-renewable resources respectively, both of them may be used indistinctly for every resource, provided it is included in the corresponding set.

A2.2.16 Balance of traded goods

When trade of energy carriers or emission permits among regions is considered, the following balance equation must be fulfilled across regions:

$$\sum_{rg} NTX_{t,rg}^{trd} = 0 \quad (63)$$

A2.3 Objective functions

The objective function is defined as the sum of all discounted costs in the system. Costs are included at the time a plant goes into operation for investments (i.e. the beginning of the period) and at the middle of the period for operation-related costs (fixed O&M, variable O&M and fuel costs). Although the LP model may accommodate region-dependent specific investment costs i_{rg}^{te} , these have to be assumed region-independent (i.e. uniquely specified at the global level) for all the technologies in the NLP formulation and for the learning technologies in the MIP formulation.

A2.3.1 Linear objective function

The objective function of the standard linear program is given as follows:

$$z = \sum_{t=1}^T \left[\sum_{rg} \left[\sum_{te} \left[I_{t,rg}^{te} * \Delta_t * i_{rg}^{te} * (1-s_t^{te}) * (1+d)^{-t*\Delta_t} + C_{t,rg}^{te} * f_{rg}^{te} * \Delta_t * (1+d)^{(-t*\Delta_t+\Delta_t/2)} + A_{t,rg}^{te} * \Delta_t * v_{rg}^{te} * (1+d)^{(-t*\Delta_t+\Delta_t/2)} \right] + \sum_{fu} R_{t,rg}^{fu} * \Delta_t * r_{t,rg}^{fu} * (1+d)^{(-t*\Delta_t+\Delta_t/2)} \right] \right] \quad (64)$$

A2.3.2 Non-linear objective function

The objective function is amended in order to include the non-linear relationship between cumulative market size and technology investment costs. The first term in the following equation is the integral of the specific investment cost curve, i.e., it relates the cumulative cost to the total cumulative capacity and computes global investment costs in a given period as the difference between two consecutive values of cumulative cost. A variant of the NLP problem may be formulated to consider learning effects also in the fixed O&M costs.

$$z = \sum_{t=1}^T \left[\sum_{te} \left[\frac{(G_t^{te})^{1-b^{te}} - (G_{t-1}^{te})^{1-b^{te}}}{1-b^{te}} * dcap^{te} * i_{rg}^{te} * (1-s_t^{te}) * (1+d)^{-t*\Delta_t} + \sum_{rg} \left[C_{t,rg}^{te} * f_{rg}^{te} * (1+d)^{-t*\Delta_t+\Delta_t/2} + A_{t,rg}^{te} * \Delta_t * v_{rg}^{te} * (1+d)^{-t*\Delta_t+\Delta_t/2} \right] + \sum_{rg} \sum_{fu} R_{t,rg}^{fu} * \Delta_t * r_{t,rg}^{fu} * (1+d)^{-t*\Delta_t+\Delta_t/2} \right] \right] \quad (65)$$

The non-linear formulation of the model is also a non-convex program and the objective function possesses several minima. Therefore, the standard solvers can identify only local optimal solutions to the problem. Global optima cannot be guaranteed.

A2.3.3 Mixed Integer Programming objective function

Unlike the previous NLP formulation that allows a common treatment for learning and non-learning (i.e. with unity progress ratio) technologies, the MIP objective function includes a separate term to account for the global investment costs of the learning technologies.

$$z = \sum_{t=1}^T \left[\sum_{teg} \left[ICOST_t^{te} * (1 - s_t^{te}) * (1 + d)^{-t*\Delta_t} \right] + \sum_{rg} \left[\sum_{neg} \left[I_{t,rg}^{te} * i_{rg}^{te} * (1 - s_t^{te}) * (1 + d)^{-t*\Delta_t} \right] + \sum_{te} \left[C_{t,rg}^{te} * f_{rg}^{te} (1 + d)^{-t*\Delta_t + \Delta_t/2} + A_{t,rg}^{te} * \Delta_t * v_{rg}^{te} * (1 + d)^{-t*\Delta_t + \Delta_t/2} \right] \right] + \sum_{fu} \left[R_{t,rg}^{fu} * \Delta_t * r_{t,rg}^{fu} * (1 + d)^{-t*\Delta_t + \Delta_t/2} \right] \right] \quad (66)$$

Where:

teg: Set of learning technologies (subset of te)

neg: Set of non-learning technologies (subset of te)

A2.4 Stochastic ERIS

Several economic, environmental and technological factors are inherently uncertain and this has to be taken into account in the modelling framework. One possible method is the scenario analysis. An alternative approach is to consider explicitly uncertainty within the model to define the decisions that have least regret under all outcomes of uncertainty. These robust decisions, which constitute a hedging strategy, can be selected with a traditional multi-stage stochastic programming model. A probability of occurrence p_s is associated to each scenario $s=1, \dots, S$ and uncertainty is assumed to be resolved at a certain point in time t_r . The decision variables are then grouped into two categories: x_1 , the decisions to be determined before the resolution of uncertainty, and $x_{2,s}$, those to be defined afterwards depending of the state of the world that finally occurs.

This problem corresponds to a two-stage stochastic problem. The decisions belonging to the first stage are common to the S scenarios and constitute the hedging strategy. This strategy is defined by minimizing the expected costs of all the different states of the world. The two-stage stochastic formulation can thus be expressed as:

$$\left\{ \begin{array}{l} \text{Min} \left[c_1^T x_1 + \sum_{s=1}^S p_s c_2^T x_{2,s} \right] \\ s.t. \\ A_0 x_1 \leq b_0 \\ A_1 x_1 + A_2 x_{2,s} \leq b_s, \quad s = 1, \dots, S, \end{array} \right. \quad (67)$$

The constraints are derived from the deterministic formulation of the model. They ensure the feasibility of decisions and link first stage decisions (x_1) with second stage decisions ($x_{2,s}$). This formulation, where uncertainty appears only on the right-hand-side b_s , corresponds to a decision tree describing, for instance, alternative CO₂ emission reduction policies (see Figure 127).

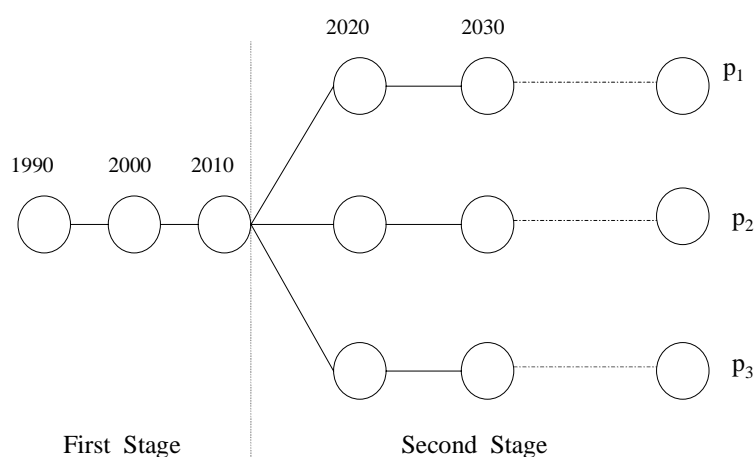


Figure 127. *Decision tree for the two-stage stochastic problem.*

The ERIS code was extended by Kypreos (1998) to include stochastic and risk aversion options. These options are defined for the linear, non-linear and MIP formulations. Their introduction into the ERIS model prototype is based on the work done previously by Van Geffen (1995) for a reduced version of the MARKAL model. The stochastic treatment was introduced for CO₂ emission reduction targets, progress ratio of learning technologies, electricity demand or a combination of the above options. For simplification, the stochastic ERIS is defined as a two-stage stochastic problem where the uncertainty on all the stochastic parameters is resolved simultaneously at a pre-specified date. If uncertainties in any of those parameters, or the learning uncertainty for different technologies, were required to be resolved at different points in time, the formulation would have to be extended to a multi-stage program.

A2.5 Changes in the ERIS code for the two-factor learning curve

In this section the changes introduced in the ERIS code to incorporate the two-factor learning curve are presented.

A2.5.1 The two-factor formulation with cumulative R&D expenditures

Here, the modifications necessary for the implementation of the two-factor formula with cumulative R&D expenditures are briefly described.

A2.5.1.1 Exogenous ARD

- Declaration and computation of parameters

PARAMETERS

- Parameters given by the user in the input file

lraterd(TE,NS)	R&D learning rate of TE per scenario
dcrd(TE)	Initial cumulative R&D expenditures

ard(TEG,NS,RT) annual R&D expenditures per technology in MUS\$

- Parameters computed by the code

c(TE,NS) learning by searching parameter
 crd(TE,NS,RT) cumulative R&D expenditures per technology

* assignment of learning by searching coefficient from R&D learning rate

$c(TE, NS) = -\log(1 - \text{lraterd}(TE, NS)) / \log(2);$

* assignment of the cumulative R&D expenditures per technology

$\text{crd}(TEG, NS, RT) = \text{dcrd}(TEG) + \sum((TT, M) \$(\text{ord}(TT) \text{ LE } \text{ord}(RT)),$
 $\text{cumcap_inv}(RT, NS, TT, M, TEG) * \text{ard}(TEG, M, TT));$
 $\text{crd}(NEG, NS, RT) = \text{dcrd}(NEG);$

- Changes to the NLP objective function

OBJNLP(NS)..

$\text{COSTNLP}(NS) = E =$

* Investment costs for learning technologies

$\text{SUM}(RTN\text{NTE}(RT, m, ns, teg),$
 $($
 $(\text{GRF}(TEG, RT, m) ** (1 - b(TEG, NS)) * (\text{crd}(TEG, NS, RT) ** (-c(TEG, NS)))) - \text{GRF}(TEG, RT,$
 $1, m) ** (1 - b(TEG, NS)) * (\text{crd}(TEG, NS, RT - 1) ** (-c(TEG, NS))))$
 $/(1 - b(TEG, NS)) * \text{dcap}(TEG) * \text{ic}(TEG, "USA") * (\text{dcrd}(TEG) ** c(TEG, NS)) * (1 -$
 $\text{salv_inv}(TEG, RT)) * (1 + \text{disc}) ** (-\text{period} * \text{time}(RT))$
 $) \$(\text{ord}(rt) \text{ gt } 1) +$
 $($
 $(\text{GRF}(TEG, "2000", m) ** (1 - b(TEG, NS)) * (\text{crd}(TEG, NS, "2000") ** (-c(TEG, NS)))) -$
 $1 * (\text{dcrd}(TEG) ** (-c(TEG, NS))))$
 $/(1 - b(TEG, NS)) * \text{dcap}(TEG) * \text{ic}(TEG, "USA") * (\text{dcrd}(TEG) ** c(TEG, NS)) * (1 -$
 $\text{salv_inv}(TEG, "2000")) *$
 $(1 + \text{disc}) ** (-\text{period} * \text{time}("2000"))$
 $) \$(\text{ord}(rt) \text{ eq } 1)$

- Changes to investment costs for learning technologies in the MIP version

* Investments to be discounted. 1st period

$\text{EQIC1}(RB, \text{TEG}, \text{NS}).. \text{ICOST}(RB, \text{TEG}, \text{NS}) = E = (\text{CCOST}(RB, \text{TEG}, \text{NS}) * (\text{crd}(TEG, NS, RB) ** (-$
 $c(TEG, NS))) - \text{ccost0}(TEG, NS) * (\text{dcrd}(TEG) ** (-c(TEG, NS)))));$

* Investments to be discounted. Other periods

$\text{EQIC2}(RT+1, \text{TEG}, \text{NS}).. \text{ICOST}(RT+1, \text{TEG}, \text{NS}) = E =$
 $(\text{CCOST}(RT+1, \text{TEG}, \text{NS}) * (\text{crd}(TEG, NS, RT+1) ** (-c(TEG, NS)))) -$
 $\text{CCOST}(RT, \text{TEG}, \text{NS}) * (\text{crd}(TEG, NS, RT) ** (-c(TEG, NS)))));$

A2.5.1.2 Endogenous ARD

- Declaration and computation of parameters

- Parameters given by the user in the input file

dcrd(TE)	Initial cumulative R&D expenditures
cmprd (TEG)	Seed for maximum growth constraint for ARD
gmprd (TEG)	Maximum growth rate for ARD
mgrrd (TEG)	Minimum growth rate for ARD
Table lraterd(TE,NS)	R&D learning rate of TE per scenario

- Parameters computed by the code

c(TE,NS)	learning by searching parameter
a(TE,NS)	coefficient of the learning curve

* assignment of learning by searching coefficient from R&D progress ratio

$$c(TE, NS) = -\log(1 - lraterd(TE, NS)) / \log(2);$$

* assignment of coefficient of the learning curve

$$a(TE, NS) = ic(TE, "USA") * (dcap(TE) ** b(TE, NS)) * (dcrd(TE) ** c(TE, NS));$$

- Declaration of new variables

POSITIVE VARIABLES

* additional variable for the learning by searching factor

ARD(ST, TEG, NS) Annual R&D expenditures per technology

CRD(ST, TEG, NS) Cummulative R&D expenditures per technology

- New equations

EQUATIONS

* additional equation for learning by searching factor

EQRDBUD(RT, NS) allocation of global R&D budget

EQCRD(RT, TEG, NS) cumulative R&D expenditures

EQGRORD(ST, NS, TEG) Maximum growth constraint ARD

EQGRLRD(ST, NS, TEG) Minimum growth constraint ARD;

* allocation of global R&D budget

$$EQRDBUD(RT_ns(RT, NS))..SUM(TEG, ARD(RT, TEG, NS)) = E = SUM(RG, GRD(RT, NS, RG));$$

* Definition of cumulative R&D expenditures

$$EQCRD(RT, TEG, NS)..CRD(RT, TEG, NS) = E = dcrd(TEG) + SUM((TT, M) \$(ord(TT) LE ord(RT)), cumcap_inv(RT, NS, TT, M, TEG) * ARD(TT, TEG, M));$$

* Maximum growth constraint Annual R&D expenditures

EQGRORD(ST_ns(ST,NS),TEG)\$ (ORD(ST) GE 2)..

ARD(ST,TEG, NS) =L= gmprd(TEG)*ARD(ST-1,TEG,NS) + cmprd(TEG);

* Minimum growth constraint Annual R&D expenditures

EQGRLRD(ST_ns(ST,NS),TEG)\$ (ORD(ST) GE 2)..

ARD(ST,TEG, NS) =G= mgrrd(TEG)*ARD(ST-1,TEG,NS);

- Changes to the NLP objective function

OBJNLP(NS)..

COSTNLP(NS) =E=

* Investment costs for learning technologies

SUM(RTNNTE(RT,m,ns,teg),

((GRF(TEG,RT,m)**(1-b(TEG,NS))*(crd(RT,TEG,NS)**(-c(TEG,NS))) - GRF(TEG,RT-1,m)**(1-b(TEG,NS))*(crd(RT-1,TEG,NS)**(-c(TEG,NS))))

/(1 - b(TEG,NS))*dcap(TEG)*ic(TEG,"USA")*(dcrd(TEG)**c(TEG,NS))*(1-salv_inv(TEG,RT))*(1+disc)**(-period*time(RT))

) \$(ord(rt) gt 1) +

((GRF(TEG,"2000",m)**(1-b(TEG,NS))*(crd("2000",TEG,NS)**(-c(TEG,NS))) - 1*(dcrd(TEG)**(-c(TEG,NS))))

/(1 - b(TEG,NS))*dcap(TEG)*ic(TEG,"USA")*(dcrd(TEG)**c(TEG,NS))*(1-salv_inv(TEG,"2000"))*

(1+disc)**(-period*time("2000"))

) \$(ord(rt) eq 1))

A2.5.2. The two-factor formulation with knowledge stock

Here the modifications to the code necessary to implement the knowledge stock function are shown.

- Declaration and computation of sets and parameters

- Set given by the user in the input file

- * Lag counter for computation of series on the depreciation rate
- * It must be specified according to the maximum rdlag in the group of
- * learning technologies. That is, if the maximum rdlag is 4
- * lcount must be given as /0*4/

SET lcount /0*0/;

- Parameters given by the user in the input file

dknow(TE)	Initial knowledge stock
cmprd (TEG)	Seed for maximum growth constraint for ARD
gmprd (TEG)	Maximum growth rate for ARD
mgrrd (TEG)	Minimum growth rate for ARD
deprate(TEG)	Annual depreciation parameter for knowledge function
rdlag(TEG)	Lag parameter for knowledge function
Table lraterd(TE,NS)	R&D learning rate of TE per scenario
Table grd(RT,NS,RG)	Regional annual R&D budget in MUS\$

- * lagged R&D expenditures required for the initialisation
- * of the knowledge stock. Values are given backwards and in relation to the
- * initial value of knowledge(dknow). That is, assuming dknow is given for 2000,
- * ardpast will be given for 2000(0), 1999(1),...etc.

Table ardpast(TEG,lcount) Past R&D expenditures

Table ARDBD(TEG,BD,NS,ET) Bounds for R&D expenditures

- Parameters computed by the code

c(TE,NS)	Learning by searching parameter
a(TE,NS)	Coefficient of the learning curve

- * parameters to compute annual knowledge stock

sdep1(TEG)	Summation of the depreciation rate series
sdep2(TEG)	Summation of the depreciation rate series

wsardp(TEG) Weighted summation of past lagged R&D expenditures

* assignment of learning by searching coefficient from R&D learning rate

$$c(TE, NS) = -\log(1 - \text{lraterd}(TE, NS)) / \log(2);$$

* assignment of coefficient of the learning curve

$$a(TE, NS) = \text{scost0}(TE, NS) * (\text{dcap}(TE) ** b(TE, NS)) * (\text{dknow}(TE) ** c(TE, NS));$$

* assignment of the summation of weights for current period ARDs

$$\begin{aligned} \text{sdep1}(TEG) \$ (\text{deprate}(TEG) \text{ NE } 0) &= (1 - (1 - \text{deprate}(TEG)) ** (\text{period-rdlag}(TEG))) / (1 - (1 - \text{deprate}(TEG))); \\ \text{sdep1}(TEG) \$ (\text{deprate}(TEG) \text{ EQ } 0) &= \text{period-rdlag}(TEG); \end{aligned}$$

* assignment of the summation of weights for previous period ARDs

$$\begin{aligned} \text{sdep2}(TEG) \$ (\text{deprate}(TEG) \text{ NE } 0) &= (1 - (1 - \text{deprate}(TEG)) ** (\text{rdlag}(TEG))) / (1 - (1 - \text{deprate}(TEG))); \\ \text{sdep2}(TEG) \$ (\text{deprate}(TEG) \text{ EQ } 0) &= \text{rdlag}(TEG); \end{aligned}$$

* assignment of the weighted summation of historical lagged ARDs

$$\text{wsardp}(TEG) = \text{sum}(\text{lcount} \$ (\text{ord}(\text{lcount}) \text{ LE } \text{rdlag}(TEG)), \text{ardpast}(TEG, \text{lcount}) * ((1 - \text{deprate}(TEG)) ** (\text{ord}(\text{lcount}) - 1)));$$

- Additional variables for the learning by searching factor

POSITIVE VARIABLES

ARD(ST, TEG, NS) Annual R&D expenditures per technology

KNOW(ST, TEG, NS) Knowledge stock per technology

- Additional equations for the learning by searching factor

EQRDBUD(RT, NS) Allocation of global R&D budget

EQKNOW1(RT, TEG, NS) Knowledge stock - first period

EQKNOW2(RT, TEG, NS) Knowledge stock - other periods

EQGRORD(ST, NS, TEG) Maximum growth constraint ARD

EQGRLRD(ST, NS, TEG) Minimum growth constraint ARD;

* allocation of global R&D budget

$$\text{EQRDBUD}(\text{RT_ns}(\text{RT}, \text{NS})) .. \text{SUM}(\text{TEG}, \text{ARD}(\text{RT}, \text{TEG}, \text{NS})) = \text{L} = \text{SUM}(\text{RG}, \text{GRD}(\text{RT}, \text{NS}, \text{RG}));$$

* Definition of knowledge stock using year-by-year lags - First period

EQKNOW1(RB,TEG,NS)..KNOW(RB,TEG,NS)=E=dknow(TEG)*((1-deprate(TEG))**(period))+
sdep1(TEG)*ARD(RB,TEG,NS) + ((1-deprate(TEG))**(period-rdlag(TEG)))*wsardp(TEG);

* Definition of knowledge stock using year-by-year lags - Other periods

EQKNOW2(RT,TEG,NS)\$(ORD(RT) GT 1)..KNOW(RT,TEG,NS)=E=KNOW(RT-1,TEG, NS)*((1-
deprate(TEG))**(period))+ sdep1(TEG)*ARD(RT,TEG,NS) + ((1-
deprate(TEG))**(period-rdlag(TEG)))*sdep2(TEG)*ARD(RT-1,TEG,NS);

* Maximum growth constraint Annual R&D expenditures

EQGRORD(ST_ns(ST,NS),TEG)\$(ORD(ST) GE 2)..
ARD(ST,TEG, NS) =L= gmprd(TEG)*ARD(ST-1,TEG,NS) + cmprd(TEG);

* Minimum growth constraint Annual R&D expenditures

EQGRLRD(ST_ns(ST,NS),TEG)\$(ORD(ST) GE 2)..
ARD(ST,TEG, NS) =G= mgrrd(TEG)*ARD(ST-1,TEG,NS);

- Changes to the non-linear objective function

* Non-linear objective function

OBJNLP(NS)..

COSTNLP(NS) =E=

* Investment costs for learning technologies

SUM(RTNNTE(RT,m,ns,teg),

(GRF(TEG,RT,m)**(1-b(TEG,NS))*(KNOW(RT,TEG,NS)**(-c(TEG,NS))) -
GRF(TEG,RT-1,m)**(1-b(TEG,NS))*(KNOW(RT-1,TEG,NS)**(-c(TEG,NS))))

/(1 - b(TEG,NS))*dcap(TEG)*scost0(TEG,NS)*(dknow(TEG)**c(TEG,NS))*(1-
salv_inv(TEG,RT))*(1+disc)**(-period*time(RT))

) \$(ord(rt) gt 1) +

((GRF(TEG,"2000",m)**(1-b(TEG,NS))*(KNOW("2000",TEG,NS)**(-c(TEG,NS))) -
1*(dknow(TEG)**(-c(TEG,NS))))

/(1 - b(TEG,NS))*dcap(TEG)*scost0(TEG,NS)*(dknow(TEG)**c(TEG,NS))*(1-
salv_inv(TEG,"2000"))*

(1+disc)**(-period*time("2000"))

) \$(ord(rt) eq 1)

)

+

* R&D investments

```
SUM(RTNNTE(RT,m,ns,teg), period*ARD(RT,TEG,m)*((1+disc)**(-period*time(RT))))  
;
```

* Initialisation of knowledge stock

```
KNOW.FX("1990",TEG, NS)=dknow(TEG);  
KNOW.LO(RT,TEG, NS)=1.0;
```

- Changes to the MODEL declaration

* Add the following lines to MODEL ERISNLP

```
EQRDBUD  
EQKNOW1  
EQKNOW2  
EQGRORD  
EQGRLRD  
/;
```


Appendix 3. Stochastic progress ratio in RMARKAL

In this section some additional aspects of the behaviour of the models with a stochastic specification of the progress ratio are highlighted, using as an example the simplified single region global electricity generation MARKAL model applied in chapter 4. The purpose is to illustrate the non-linear response of the model when the probabilities of occurrence of the different states-of-the-world are modified.

The two-stage stochastic programming formulation applied above for the ERIS model is also used in MARKAL. The stochastic treatment is applied only to the progress ratio of the solar PV technology. Three states of the world have been considered. An "optimistic" progress ratio of 0.72, a medium value of 0.81 and a "pessimistic" one of 0.90. The resolution of the uncertainty occurs in the year 2030. The results of the three deterministic cases and the corresponding stochastic one are compared here.

Figure 128 presents the cumulative installations of solar PV under the stochastic case in comparison to the corresponding deterministic cases. If a deterministic progress ratio of 0.90 is specified, the technology is clearly not attractive and remains marginal. But, with a progress ratio of 0.81, penetration already occurs along the maximum growth constraint. Obviously, with PR=0.72 the costs reduction is even more attractive and the technology also grows at its maximum. When the two-stage stochastic model is run, specifying equal probabilities of occurrence for the three states of the world, the model chooses vigorous early growth as the hedging path. The presence and weight of the PR=0.81 and PR=0.72 states of the world offset the effects of the PR=0.90 one and the technology results attractive.

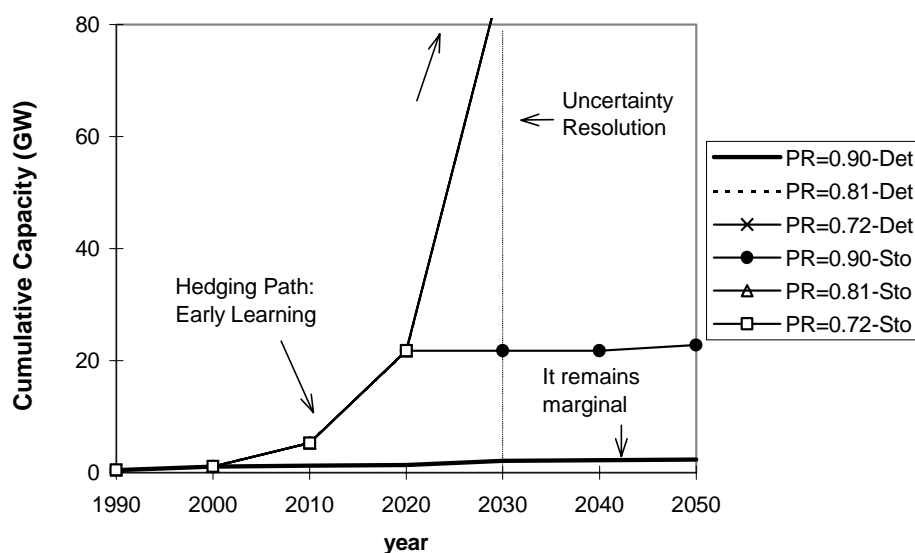


Figure 128. Cumulative capacity. Deterministic Vs Stochastic cases. Equal probabilities of occurrence.

However, the result is sensitive to the specification of the probabilities weighting each of the states of the world. In order to illustrate this, the following experiment was carried out. The probability of occurrence of the PR=0.72 state was varied at small intervals. The probabilities of the two other states were adjusted accordingly, being kept

equal to each other. The result is shown in Figure 129. A highly non-linear response of the model can be observed there. For probabilities of PR=0.72 below 0.14, the "pessimistic" state of the world (PR=0.90) dominates and even in the hedging path the technology remains marginal. But, for values above 0.14, in the first stage hedging path the capacity grows at the maximum growth rate, as in the deterministic states PR=0.81 and PR=0.72. The response of the model is in this case "non-smooth". That is, there is not a gradual increase of the penetration of the technology as the probability is increased, but a sudden change occurs. Although here it is not claimed that this is a typical situation, it is highlighted that such behaviour may occur when the increasing returns mechanism is present. Even in the stochastic framework, where it could be more likely for the model to follow an intermediate path, small changes may trigger the vigorous positive feedback caused by the learning mechanism, resulting in a response dominated by an "optimistic" state of the world. Or, vice versa, a "pessimistic" state of the world may dominate the situation, resulting in a complete lack of incentive to deploy the technology.

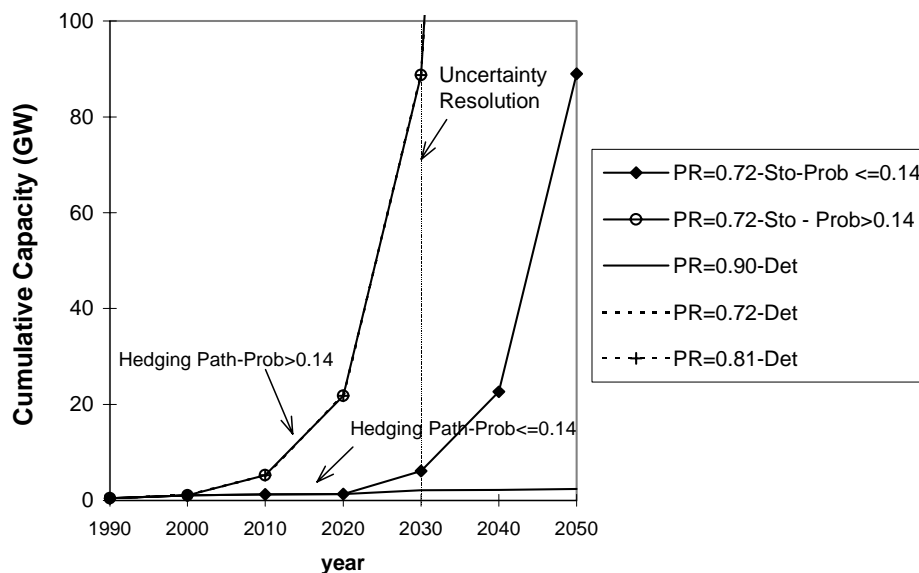


Figure 129. Cumulative capacity. Deterministic Vs Stochastic cases. Variation of probabilities of occurrence.

Of course, other factors may intervene and alter or smooth such behaviour. An additional example allows illustrating this. The runs above were made with the specification of an annual availability factor. That is, the technology is considered to exhibit the same availability all year round. In the case of solar PV this may be an unrealistic representation, since the solar radiation reaching the ground is likely to exhibit a seasonal behaviour. But the MARKAL model allows the specification of (up to six) seasonal availability factors in order to reflect that in some seasons and regions (e.g. winter in the northern hemisphere), the availability of the resource can be lower. With the specification of availability factors per season in our example the response depicted in Figure 130 was obtained, considering equal probabilities for all the states of the world. The model exhibits now a much more "smooth" response and follows an intermediate path of installations in the stochastic case.

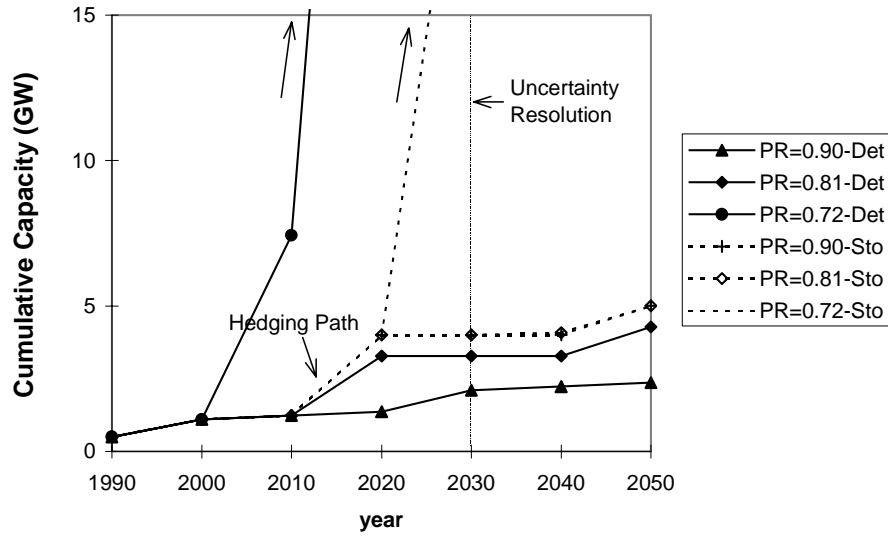


Figure 130. Cumulative capacity. Deterministic Vs Stochastic cases. Equal probabilities of occurrence. Seasonal availability factor for the technology.

Appendix 4. Another approach to learning uncertainty in the ERIS Model

As a complement to the stochastic learning analyses performed above, the implementation of the resolution of uncertainty in the learning rates as a function of cumulative capacity in the ERIS model is presented here. The approach is described, some results for a simplified global electricity generation system are shown and some insights and limitations outlined. The presentation is only illustrative, as no detailed analyses were performed following this approach.

A4.1 Description of the approach

The endogenisation of learning effects provides a significant improvement in the treatment of the technological dynamics but it has a weakness. The whole approach is highly sensitive to the value of the progress ratio that is assumed known. Stochastic programming becomes an alternative to deal with the uncertainty associated to this parameter. Scenario analysis remains, of course, another pursuable option.

Following the approach applied by Mattsson (1998) for the GENIE Model, resolution of uncertainty is performed here as a function of cumulative capacity and not of time. The rationale behind such formulation is that only the accumulation of experience will allow gaining information about the actual learning rates of a given technology.

For this analysis learning uncertainty has been considered only for two technologies. Uncertainty is resolved for each individual technology after a pre-specified cumulative capacity threshold. The problem is solved as a three-stage stochastic Mixed Integer Programming model. The first stage is defined as the set of periods before any of the technologies crosses the cumulative capacity threshold. In the second stage only one of them has crossed the threshold. In the third one both of them have done so. If learning uncertainty were to be implemented for N technologies following this approach, the problem would become a $N+1$ -stages one. A new stage is reached when a certain technology surpasses its own cumulative capacity threshold and the corresponding uncertainty is resolved. Here, no attempt to devise or test such generalised formulation has been made. A multi-stage problem would also arise if learning uncertainty were to be combined with uncertainty in other factors such as GHG emissions or energy demand.

The definition of the problem poses some difficulties compared to the usual stochastic approach where uncertainties are resolved at a certain point in time. Uncertainties in the progress ratio are to be resolved when the cumulative capacity (a variable) reaches a certain threshold. That is, there is no fixed time period (a parameter) distinguishing the first stage from the second or third stages. The extension of each stage will be determined endogenously. Therefore, logical conditions defining the transition from one stage to the other are necessary. They are implemented here using binary variables in a similar way as the logical conditions related to the curve segmentation (Williams, 1985, Sierksma, 1996). The basic relations are given by equations (68) and (69) below:

$$C_{te,t} + (C_{te,max} - C_{te,thres}) * \delta_{te,stage} \leq C_{te,max} \quad (68)$$

$$C_{te,t} - (C_{te,0} - C_{te,thres}) * \delta_{te,stage} \geq C_{te,thres} + \varepsilon * (1 - \delta_{te,stage}) \quad (69)$$

Where:

- $C_{te,t}$: Cumulative capacity for the technology te at time t
- $C_{te,max}$ Maximum cumulative capacity
- $C_{te,0}$ Initial cumulative capacity
- $C_{te,thres}$ Cumulative capacity threshold for uncertainty resolution
- $\delta_{te,stage}$ Binary variable for stage definition {0,1}
- ε Small positive number

From equation (68) follows:

$$\begin{aligned} C_{te,t} \leq C_{te,thres} &\Rightarrow \delta_{te,stage} = 1 \\ C_{te,t} \leq C_{te,max} &\Rightarrow \delta_{te,stage} = 0 \end{aligned} \quad (70)$$

From equation (69):

$$\begin{aligned} C_{te,t} \geq C_{te,0} &\Rightarrow \delta_{te,stage} = 1 \\ C_{te,t} \geq C_{te,thres} + \varepsilon &\Rightarrow \delta_{te,stage} = 0 \end{aligned} \quad (71)$$

The combination of equations (68) and (69) gives the representation of the following logical condition:

$$\begin{aligned} C_{te,0} \leq C_{te,t} \leq C_{te,thres} &\Leftrightarrow \delta_{te,stage} = 1 \\ C_{te,thres} + \varepsilon \leq C_{te,t} \leq C_{te,max} &\Leftrightarrow \delta_{te,stage} = 0 \end{aligned} \quad (72)$$

For each technology with uncertain learning rate, a corresponding binary variable $\delta_{te,stage}$ is designated and equations (68) and (69) have to be specified.

An additional variable denominated stage is defined as:

$$stage = 1 + \sum_{te} (1 - \delta_{te,stage}) \quad (73)$$

Also, using this formulation, additional logical conditions are specified in order to ensure the consistency of the variables in the different stages (e.g. first stage variables should be equal for all scenarios, etc.).

A4.2 General assumptions

The analysis is performed for a simplified model of the global electricity system. The electricity demand corresponds to the electricity production of the scenario B (“middle-course”) presented in IIASA/WEC (1998). With the exception of the gas fuel cell, for which a different basis progress ratio is specified (PR=0.85), all technologies have the same characteristics as in the analyses in chapter 4.

Learning uncertainty has been considered for solar photo-voltaics and the gas fuel cell. Both emerging technologies have the opportunity/challenge to gain a sizeable share on the electricity market in the future, providing power with an efficient use of resources

and reduced environmental impacts, but this will depend upon their ability to compete effectively. Significant potential for cost reduction is at hand, but its exact magnitude is uncertain.

Two values of the progress ratio have been considered for each of these technologies. The combination of them totals four states of the world in the model. Table 11 presents the progress ratios used for this analysis. Figure 131 shows the corresponding learning curves. Here, all the scenarios are considered equally probable. But, clearly, in more elaborate analyses criteria have to be discussed for assigning probabilities of occurrence to different progress ratios. The other sensitive assumption corresponds to the cumulative capacity threshold for uncertainty resolution. Here, $C_{te,thres}$ is assumed to be 50 GW for both technologies in the first tests. A sensitivity analysis for both the probabilities of occurrence and the cumulative capacity threshold is presented below in numeral A4.4.

Technology	Progress Ratio	
Solar Photo-Voltaics	0.81	0.90
Gas Fuel Cell	0.85	0.90

Table 11. *Progress ratios for uncertainty analysis.*

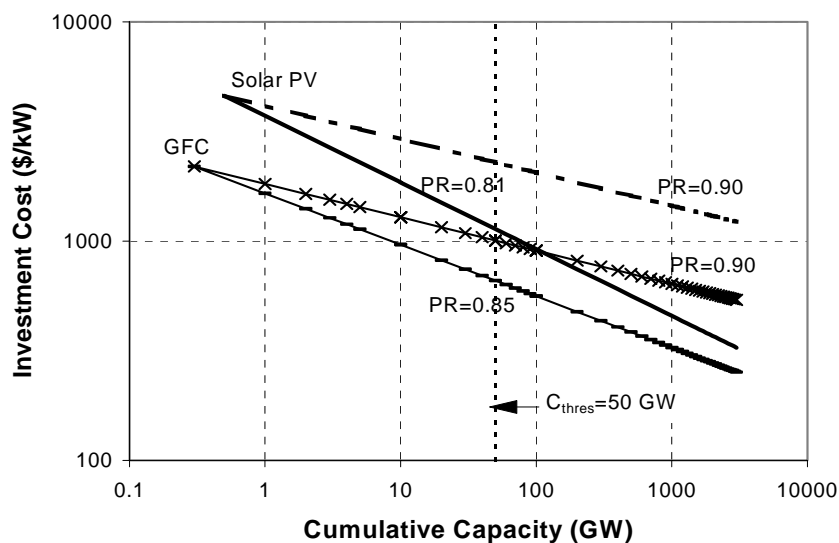


Figure 131. *Learning curves for solar PV and gas fuel cell.*

A4.3 Some results

Some results concerning the behaviour of both technologies with this three-stage programming approach are presented in this section. Only a Business-as-Usual (BaU) scenario is considered, with no CO₂ emissions constraint applied.

Figure 132 and Figure 133 present the evolution of the cumulative capacity (in logarithmic scale) in the stochastic case for the two technologies with uncertain

learning. Both technologies are introduced and surpass (or reach) the threshold simultaneously in 2030. Thus, in this particular case the model passes directly from the first to the third stage. The gas fuel cell proves to be a very attractive option for this system, growing along (or very close to) its maximum growth constraint in all states of the world. Solar PV, on the other hand, does not grow beyond the threshold for those scenarios where it has a high progress ratio. Still, as the possibility of an attractive progress ratio exists, the model considers optimal to make the investments that resolve its learning uncertainty.

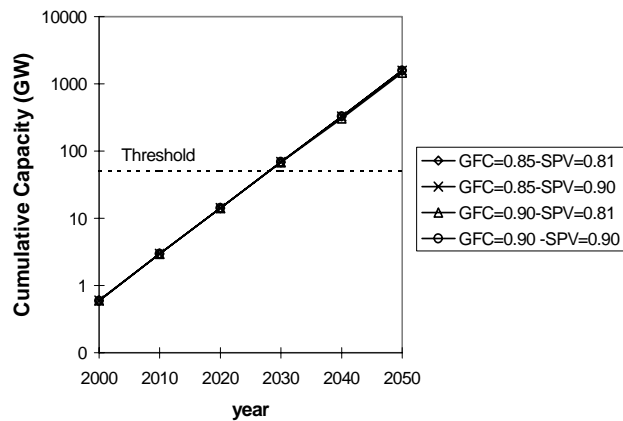


Figure 132. *Evolution of the cumulative capacity. Gas fuel cell. Stochastic case.*

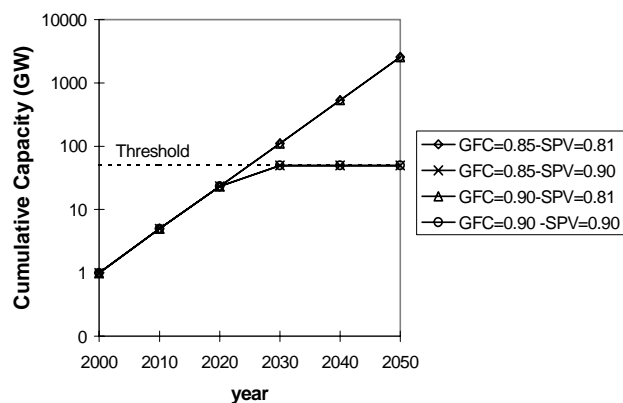


Figure 133. *Evolution of the cumulative capacity. Solar PV. Stochastic case.*

A comparison with the deterministic cases is important to appreciate the outcome of the stochastic approach. Figure 134 and Figure 135 present the evolution of the corresponding cumulative capacities when deterministic learning rates are assumed. Although the gas fuel cell is present in all scenarios, its growth is significantly lower for the scenario where both technologies have high progress ratios. On the other hand, solar PV does not enter at all into the solution in the two scenarios where its progress ratio is high. Clearly, in the first stage the stochastic model carries out installations of solar PV and gas fuel cells as a hedging strategy against their learning uncertainty.

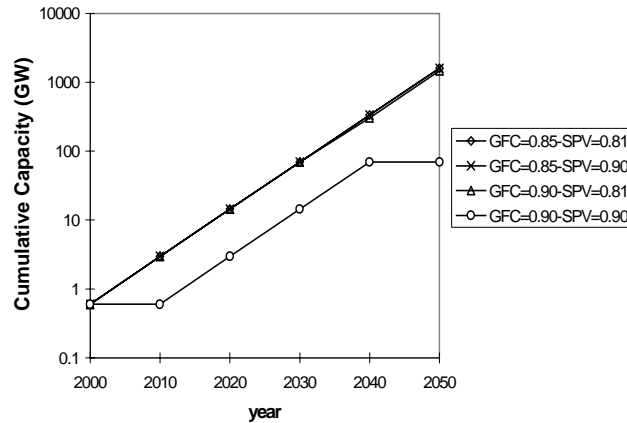


Figure 134. *Evolution of the cumulative capacity. Gas fuel cell. Deterministic cases.*

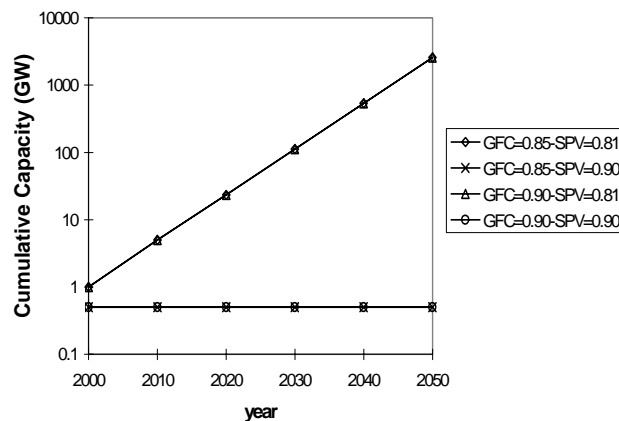


Figure 135. *Evolution of the cumulative capacity. Solar PV. Deterministic cases.*

A4.4 Some sensitivities

Besides the progress ratio, several other parameters in this approach are also uncertain and sensitivity analyses are required to address their influence. Here, for illustrative purposes, sensitivities to the probability of occurrence and the cumulative capacity threshold are performed. An additional interesting sensitivity analysis would be related to the "states of nature" being selected, that is the different values of progress ratios involved for each technology. Such kind of analysis, however, was not undertaken here.

A4.4.1 Cumulative capacity threshold

As mentioned above, the cumulative capacity threshold defines the amount of experience required to resolve the uncertainty in the progress ratio for a given technology. For the previous analysis the cumulative capacity threshold was assumed at 50 GW. Here, sensitivities are considered. The probabilities of occurrence for the different states of the world are kept equal.

Table 12 presents the cumulative capacities that solar PV and gas fuel cell reach by the end of the horizon (year 2050) when different cumulative capacity thresholds are employed. In all the cases examined here, the model always found cost-effective to

reach the minimum value of installed capacity that allows resolving the corresponding learning uncertainty for both technologies. However, different specifications of the threshold drove to notable variations in the resulting installations along the horizon. In general, a higher threshold produced lower installations of the corresponding technology.

Scenario (PR)		Cumulative Capacity – 2050									
GFC	SPV	GFC	SPV	GFC	SPV	GFC	SPV	GFC	SPV	GFC	SPV
0.85	0.81	1605.	2578.	1581.	2567.	1605.	2304.	1605.	2304.	1605.	2578.
0.85	0.90	1605.	10	1581.	50	1605.	100	1605.	100	1605.	10
0.90	0.81	1453.	2578.	1468.	2567.	1480.	2304.	1480.	2304.	1453.	2578.
0.90	0.90	1605.	10	1581.	50	219.2	100	1605.	100	191.7	10
C_{thres} (GW)		10	10	50	50	100	100	10	100	100	10

Table 12. *Cumulative capacities in 2050. Different capacity thresholds.*

For instance, when the capacity threshold is increased to 100 GW for both technologies, solar PV is installed at least up to this value, remaining at the threshold for the scenarios where its progress ratio is high. On the other hand, the gas fuel cell reaches installations above the capacity threshold for all the scenarios. However, in the fourth scenario, where both technologies exhibit high progress ratio, the cumulative capacity reached is significantly lower than the ones obtained with C_{thres} at 10 or 50 GW levels. Thus, an increase in the amount of cumulative experience needed to gain information, i.e. a later and more costly procurement of the information regarding the progress ratio, does not encourage the model to install more gas fuel cell capacity. By the same token, an earlier and cheaper realisation of this information allows the model to take action sooner and higher investments can be made.

A4.4.2 Probability of occurrence

So far, the probabilities of occurrence have been assumed equal for all the realisations of the progress ratio. Here, the effects of assigning different probabilities are examined (see Table 13). The probabilities specified for the four states of nature result from the combination of the individual probabilities for each realisation of the progress ratio of the individual technologies. It must be noticed that not all the possible combinations were used in the analysis, but only a small set was selected. The cumulative capacity threshold considered was 50 GW for both technologies.

Case	Progress Ratio				State of the World			
	SPV		GFC					
	0.81	0.90	0.85	0.90	GFC=0.85, SPV=0.81	GFC=0.85, SPV=0.90	GFC=0.90, SPV=0.81	GFC=0.90, SPV=0.90
1	0.01	0.99	0.01	0.99	0.0001	0.0099	0.0099	0.9801
2	0.1	0.9	0.1	0.9	0.01	0.09	0.09	0.81
3	0.2	0.8	0.2	0.8	0.04	0.16	0.16	0.64
4	0.3	0.7	0.3	0.7	0.09	0.21	0.21	0.49
5	0.4	0.6	0.4	0.6	0.16	0.24	0.24	0.36
6	0.5	0.5	0.5	0.5	0.25	0.25	0.25	0.25
7	0.6	0.4	0.6	0.4	0.36	0.24	0.24	0.16
8	0.7	0.3	0.7	0.3	0.49	0.21	0.21	0.09
9	0.8	0.2	0.8	0.2	0.64	0.16	0.16	0.04
10	0.9	0.1	0.9	0.1	0.81	0.09	0.09	0.01
11	0.99	0.01	0.99	0.01	0.9801	0.0099	0.0099	0.0001

Table 13. Selected probabilities for the sensitivity analysis.

Table 14 and Table 15 present the cumulative capacity of solar PV and the gas fuel cell reached at the end of the horizon in the different states of the world for the different combinations of probabilities of Table 13. As expected, changing the probabilities of occurrence modifies the outcome of the model. However, variations do not appear to be "smooth".

Case	State of the World			
	GFC=0.85, SPV=0.81	GFC=0.85, SPV=0.90	GFC=0.90, SPV=0.81	GFC=0.90, SPV=0.90
1	50.	50.	50.	50.
2	1479.43	50.	1444.52	50.
3	2254.77	50.	2254.77	50.
4	2578.14	50.	2578.14	50.
5	2578.02	50.	2578.02	50.
6	2566.71	50.	2566.71	50.
7	2578.14	50.	2578.14	50.
8	2578.14	50.	2578.14	50.
9	2578.14	50.	2578.14	50.
10	2578.14	50.	2578.14	50.
11	2578.14	50.	2578.14	50.

Table 14. Cumulative capacity for solar PV in 2050. Different probabilities.

State of the World				
Case	GFC=0.85, SPV=0.81	GFC=0.85, SPV=0.90	GFC=0.90, SPV=0.81	GFC=0.90, SPV=0.90
1	1605.19	1605.19	1605.16	1605.16
2	1605.16	1605.16	1421.07	1605.16
3	1605.16	1605.16	1482.93	745.0
4	1596.83	1605.16	1468.3	123.91
5	1596.86	1605.16	1467.94	1605.16
6	1580.84	1581.35	1467.6	1581.35
7	1596.82	1605.16	1468.07	326.06
8	1596.82	1605.16	1467.93	181.44
9	1589.36	1605.16	1482.73	201.59
10	1605.16	1605.16	1482.87	206.79
11	1605.16	1605.16	1482.87	206.79

Table 15. *Cumulative capacity for gas fuel cell in 2050. Different probabilities.*

Again, in all the cases examined here the model invested in capacity for both technologies to reach at least the uncertainty resolution threshold. In the case of solar PV, the installations remain there for the states of the world with "pessimistic" progress ratio but are substantially higher for those with an "optimistic" progress ratio. Only when the pessimistic state presents a very high probability is the cumulative capacity in the "optimistic" state affected. When such probability is 0.9 the amount installed is substantially lower. When it is assigned to 0.99 the cumulative capacity remain at the threshold for all states of the world. Thus, under the particular circumstances examined here, the presence of the optimistic state of the world appears to dominate the outcome.

The installation of the gas fuel cell is also affected by the weight of the "pessimistic" state but not so substantially as in the case of solar PV.

A4.5 Some remarks

An illustrative example of the implementation of uncertain learning in the ERIS model using an alternative formulation is presented. Uncertainty for two learning technologies is resolved as a function of a cumulative capacity threshold. The corresponding three-stage stochastic MIP problem is formulated and solved. The results confirm the importance of introducing a stochastic treatment for the learning rates. In deterministic scenarios the model does not introduce learning technologies without sufficiently attractive learning rates, and tries to get the maximum of those technologies with the lowest ones instead. The stochastic approach seems to follow a more balanced approach, diversifying the technology choice and favouring the installation of critical amounts of capacity in order to hedge against their uncertain learning rates. Such critical investments allow the accumulation of the experience necessary to resolve the learning uncertainty. An earlier and less costly gathering of the information regarding learning rates allows the model to act sooner.

However, the approach followed here significantly increases the computational effort to solve it. The number of binary variables involved in the problem increases substantially if more states of nature are added to the discrete probability distribution or more

technologies with uncertain progress ratios are considered. The latter factor also increases the number of stages and drives to the specification of additional constraints. Therefore, it is important to explore the application of other forms of stochastic programming for the uncertainty of the learning rates.

In addition, there is a significant sensitivity to the value assigned to the capacity threshold. The model decides whether it is cost-effective or not to install a given technology at least up to the specified capacity threshold, in order to resolve the learning uncertainty. Thus, the specification of a different threshold may drive the model to a higher/lower installation of capacity. The sensitivity of the model to this parameter should be handled carefully, as it is difficult to determine how much accumulation of knowledge is really required to resolve the progress ratio uncertainty (the threshold parameter is itself uncertain). Also, the outcome of the model is sensitive to the weights given to the different states of the world. Nonetheless, the implementation of a stochastic approach conditioning the resolution of uncertainty on the attainment of a certain installed capacity is in line with the fact that actual experience is required in order to establish the real possibilities of cost/performance improvements for a given technology.

Appendix 5. Description of the multi-regional MARKAL energy database

The database used for the analysis presented in the chapter 8 is briefly described here. A simplified multi-regional MARKAL model of the global energy system has been set up, being trade of emissions and energy carriers (oil, gas, coal) allowed across regions.

Five regions are considered. Two regions represent the industrialised countries: North America (NAM) and the rest of the countries belonging to the OECD in 1990 (OOECD). OOECD comprises Western Europe and the so-called Pacific OECD region (which includes Japan, Australia and New Zealand). One region represents the economies-in-transition, putting together the Former Soviet Union and Eastern Europe (EEFSU). The developing world is grouped in two additional regions. Developing countries in Asia are included in the ASIA region. ASIA comprises centrally planned Asia, South East Asia and Pacific Asia. The rest of the world is covered in the LAFM region, which includes Latin America, Africa and the Middle East.

The regions are aggregates of the eleven regions used in the IIASA-WEC (1998) study. The description of such regionalisation and a detailed listing of the countries belonging to each region can be found there. The grouping is based on work carried out at IIASA (see, for instance, Riahi and Roehrl, 2000 and Roehrl and Riahi, 2000). The bulk of the data comes from the corresponding MESSAGE model databases, kindly made available to the author by the ECS Project at IIASA¹⁰⁰. Data and modelling are not identical for all the technologies, however and many technologies present in the MESSAGE model could not be included in the compact MARKAL one. Therefore, results should not be expected to match. Obviously, any shortcomings of the analysis presented here remain the sole responsibility of the present author.

The model horizon is 1990-2050. The starting year has been calibrated according to available historical values, using the databases available online from the IIASA-WEC (1998) study. Ten-year periods are considered and a discount rate of 5% is applied to the calculations.

The demand projections and fossil fuel resources correspond to those applied in the MESSAGE characterisation of the B2 storyline of the SRES study (IPCC, 2000, Riahi and Roehrl, 2000). B2 is a "dynamics-as-usual" scenario, where differences in the economic growth across regions are gradually reduced and concerns for environmental and social sustainability at the local and regional levels rise along the horizon. Population growth is consistent with the United Nations median projection increasing to 9.4 billion people in 2050 in a continuation of historical trends. Economic growth is gradual. World GDP increases at an average rate of 2.8% per annum between 1990 and 2050. It grows from 20.9 trillion US (1990) dollars in 1990 to 109.5 trillion in 2050 (at market exchange rates). Income per capita grows at a global average of 1.8% per year

¹⁰⁰ Both four-region and eleven-region versions of the MESSAGE model were used as follows. EEFSU, ASIA and LAFM regions were built from the corresponding four-region model databases. NAM and OOECD regions were taken from the eleven-region model, the latter as an aggregation of the Western Europe (WEU) and Pacific OECD (PAO) databases.

for the same period reaching an average value of 11700 US (1990) dollars in the year 2050 (at market exchange rates). The process of gradual convergence between developing and developed regions moves forward along the horizon but significant differences still exist in 2050.

Energy needs for industrial, residential, commercial and transportation sectors are considered. Residential and commercial sectors are merged in a single one referred to as Res./Comm. For both the industrial and Res./Comm. sectors thermal and non-thermal uses are distinguished. A simplified transportation sector aggregates both freight and passengers transport demands. Thus, as no distinction of individual modes is made, only generic technologies are specified. An additional category representing non-commercial uses of biomass is included. In total, six end-use demand sectors are considered. Non-energy feedstocks are included as an additional sector.

- Residential/Commercial thermal uses
- Residential/Commercial specific uses (mainly electricity or its substitutes)
- Industrial Thermal Uses
- Industrial Specific Uses
- Transportation
- Non-commercial energy uses (biomass)
- Non-energy feedstocks (mainly oil products)

The end-use demands per region are presented in Figure 136 to Figure 140. Figure 141 presents the aggregate global demands per sector. It must be noticed that, unlike the other categories, transportation demand is presented at the level of final energy.

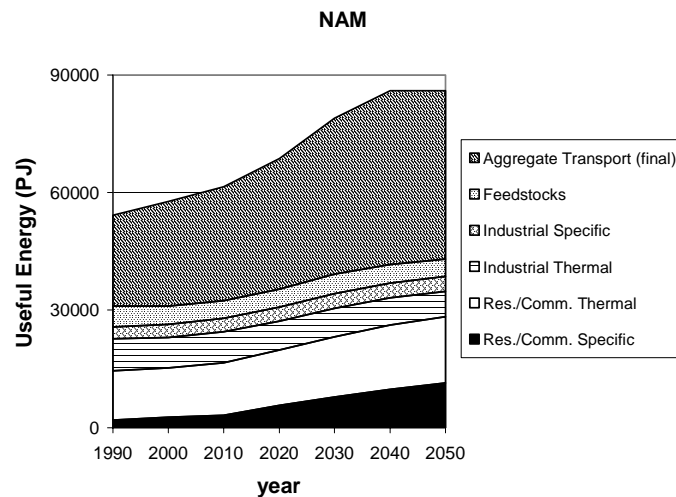


Figure 136. *End-use demands – NAM region.*

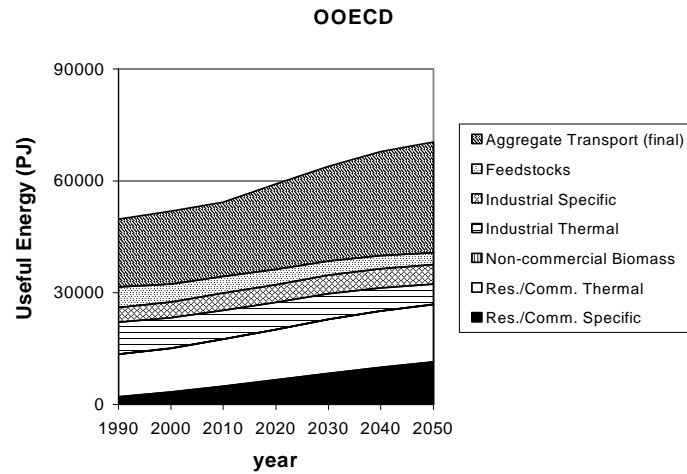


Figure 137. *End-use demands – OECD region.*

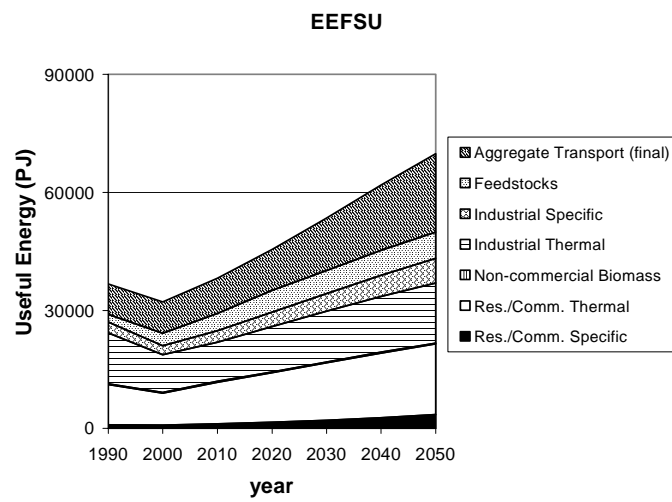


Figure 138. *End-use demands – EEFSU region.*

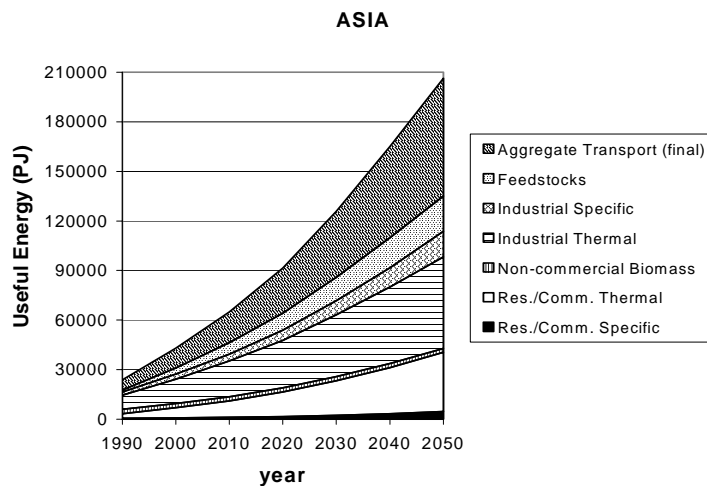


Figure 139. *End-use demands – ASIA region.*

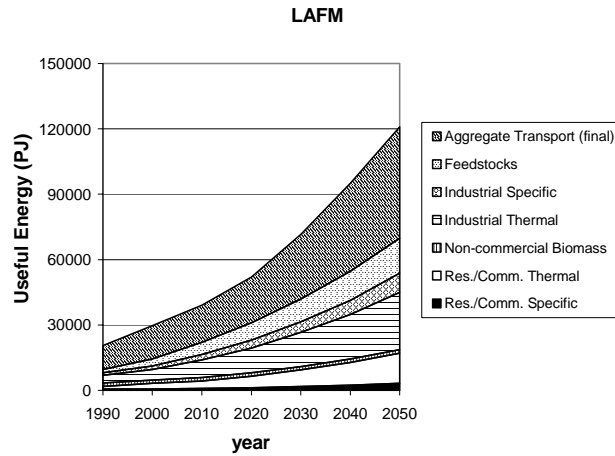


Figure 140. *End-use demands – LAFM region.*

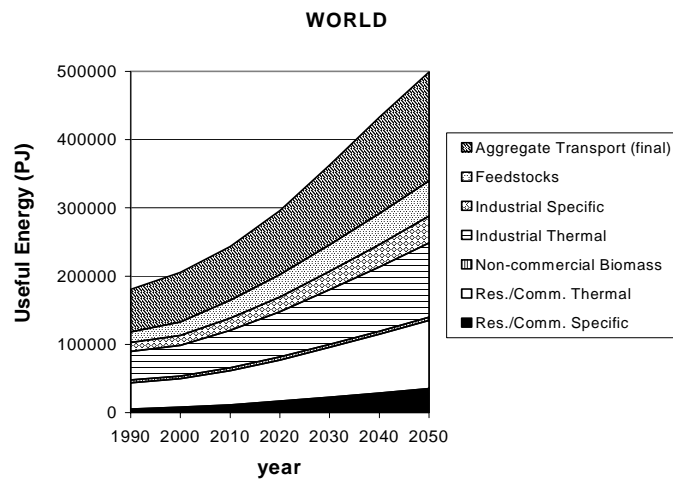


Figure 141. *Global end-use demands.*

Finally, Figure 142 presents the regionalised global aggregate demand. It is evident the increasing role that developing regions assume in the global energy markets along the time horizon in the scenario considered here.

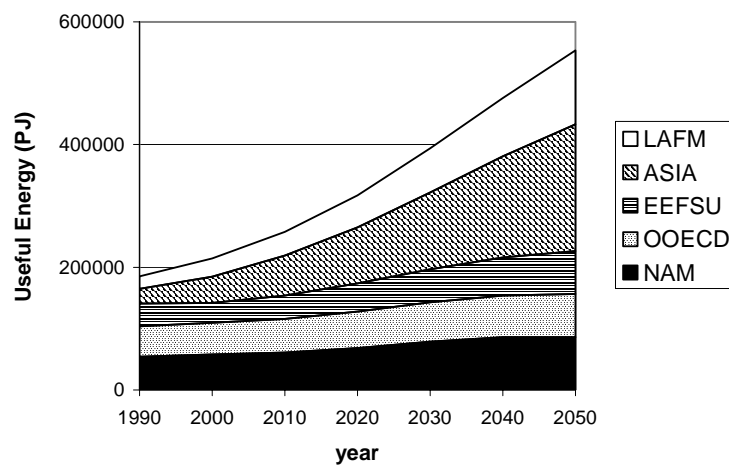


Figure 142. *Regionalised total global useful energy demand.*

Table 16 presents the annual average growth rates of the end-use demands in the different regions and at the global level for the 1990-2050 period.

	NAM	OECD	EEFSU	ASIA	LAFM	WORLD
Res./Comm. Specific	3.04	2.87	2.26	3.95	3.11	3.18
Res./Comm. Thermal	0.50	0.50	0.94	4.28	4.03	1.61
Non-commercial Biomass	n.a.	0.26	0.57	-0.15	0.06	-0.04
Industrial Thermal	0.40	-0.74	0.28	3.16	3.42	1.61
Industrial Specific	0.36	0.43	1.41	3.55	3.39	1.88
Feedstocks	-0.29	-0.93	2.00	5.04	4.01	2.03
Aggregate Transport (final)	1.03	0.82	1.59	4.11	2.59	1.58

Table 16. Annual average growth rates of end-use demands per region for the 1990-2050 period (% per annum).

As primary resources, fossil (coal, oil, natural gas), renewable resources (solar, wind, hydro, biomass) and Uranium are included. Different cost/volume categories of fossil resources are considered. The categorisation follows essentially the work of Rogner (1997). Conventional and unconventional occurrences for oil and natural gas are considered. Conventional occurrences are "those that can be exploited with current technology and present market conditions". They correspond to categories I-IV in the Table 17 but are subdivided as follows. Categories I-III represent conventional resources while category IV represents the amount that could be extracted if (existing) enhanced recovery methods are applied to those conventional resources. Unconventional occurrences "cannot be tapped with conventional production methods, because of technical or economic reasons or both". They are represented here only by categories V and VI. The categories labelled "additional occurrences" in Rogner (1997) are not included, due to the uncertainty associated to their amount and extraction costs. In total, the first five categories are considered for oil and six categories for natural gas as follows:

- Category I: Proved Recoverable Reserves
- Category II: Estimated Additional Reserves
- Category III: Additional Speculative Resources
- Category IV: Enhanced Recovery (of conventional resources)
- Category V: Recoverable Reserves (unconventional resources)
- Category VI: Resources (unconventional resources)

As for coal, two grades are distinguished: Hard coal and lignite (also known as brown coal). Five categories are considered for each of them as follows:

- Category I: Proved Recoverable Reserves
- Category II: Additional Recoverable Resources
- Category III: Additional Identified Reserves
- Category IV: Additional Resources
- Category V: Remaining Occurrences

Table 17 summarises the regionalised cumulative fossil resource availability considered here for the analysis.

Cumulative Fossil Resources (EJ)						
	NAM	OECD	EEFSU	ASIA	LAFM	World
Oil						
• Category I	449	287	861	403	4802	6802
• Category II	478	1188	785	320	1410	4181
• Category III	282	150	836	468	1771	3507
• Category IV	746	232	1135	516	3524	6153
• Category V	456	276	200	125	1104	2161
Total	2411	2133	3817	1832	12611	22804
Nat. Gas						
• Category I	493	394	1666	336	2501	5390
• Category II	599	227	1914	428	1524	4692
• Category III	652	332	2769	613	2055	6421
• Category IV	350	145	868	182	782	2327
• Category V	2135	1020	1626	1067	1267	7115
• Category VI	3469	2187	2854	1401	2860	12771
Total	7205	3911	10031	3691	8488	33326
Hard Coal						
• Category I						15594
• Category II	5865	1586	4578	1782	1783	10078
• Category III	0	6301	900	2824	53	21688
• Category IV	4371	1320	2019	12308	1670	37813
• Category V	4056	3897	21559	7213	1088	151256
Total	16226	15590	86235	28852	4353	236429
	30518	28694	115291	52979	8947	
Lignite						
• Category I						3132
• Category II	509	752	1234	636	1	2346
• Category III	0	986	151	1208	1	1593
• Category IV	126	383	180	903	1	3606
• Category V	1164	39	1866	523	14	14421
Total	4655	157	7462	2092	55	25098
	6454	2317	10893	5362	72	

Table 17. Cumulative fossil resources availability (adapted from Rogner, 1997).

Table 18 presents the regionalised annual potentials for renewable resources applied in the model.

Annual Renewable Potentials (PJ)							
	1990	2000	2010	2020	2030	2040	2050
NAM							
• Hydro	2088	2151	2303	2440	2561	2666	2756
• Wind	1441	1964	2555	3146	3677	4111	4437
• Solar electric	108	162	327	636	1162	1922	2796
• Solar thermal	167	178	437	1050	2381	4813	8119
• Biomass	3785	6029	9057	12617	16193	19258	21550
OECD							
• Hydro	2200	2660	2939	3113	3241	3337	3411
• Wind	716	1750	2754	4286	5635	7378	9668
• Solar electric	72	239	431	774	1095	1564	2246
• Solar thermal	438	1548	3022	5885	8361	11834	16514
• Biomass	3049	5746	8238	11680	14931	18749	23262
EEFSU							
• Hydro	1066	1479	2122	2937	3885	4887	5841
• Wind	307	531	870	1317	1817	2280	2640
• Solar electric	32	33	65	129	238	552	966
• Solar thermal	126	153	401	1009	2384	4983	8577
• Biomass	1801	3470	6788	12334	19033	25297	29836
ASIA							
• Hydro	1069	2176	3283	4394	5447	6504	7557
• Wind	25	785	1545	2309	2466	2627	2785
• Solar electric	0	691	1375	2063	6248	10430	14619
• Solar thermal	0	2094	4189	6283	15243	24201	33164
• Biomass	29831	32664	35771	39173	43405	48165	53523
LAFM							
• Hydro	1655	2364	3450	4762	6121	7413	8514
• Wind	263	614	1257	2085	2778	3191	3399
• Solar electric	133	204	442	979	1855	3331	5244
• Solar thermal	838	1551	2887	5160	8591	12982	17671
• Biomass	14647	21467	34035	51331	72099	93462	112384
WORLD							
• Hydro	8078	10831	14099	17645	21256	24807	28080
• Wind	2753	5645	8982	13143	16374	19586	22930
• Solar electric	345	1330	2639	4582	10599	17800	25871
• Solar thermal	1569	5523	10935	19388	36961	58813	84045
• Biomass	53112	69376	93890	127136	165662	204931	240555

Table 18. Annual regional renewable potentials.

The supply sector is represented with some detail. Technologies for the production of electricity, heat and a variety of final fuels (oil products, alcohol, hydrogen, natural gas) from several fossil and non-fossil sources are included, as well as the corresponding transmission and distribution chains. Investment, fixed O&M and variable O&M costs are considered for all the different supply technologies. A schematic representation of the standard Reference Energy System (RES) used for all the regions, containing all the possible energy chains that can be chosen by the model, is shown in Figure 143.

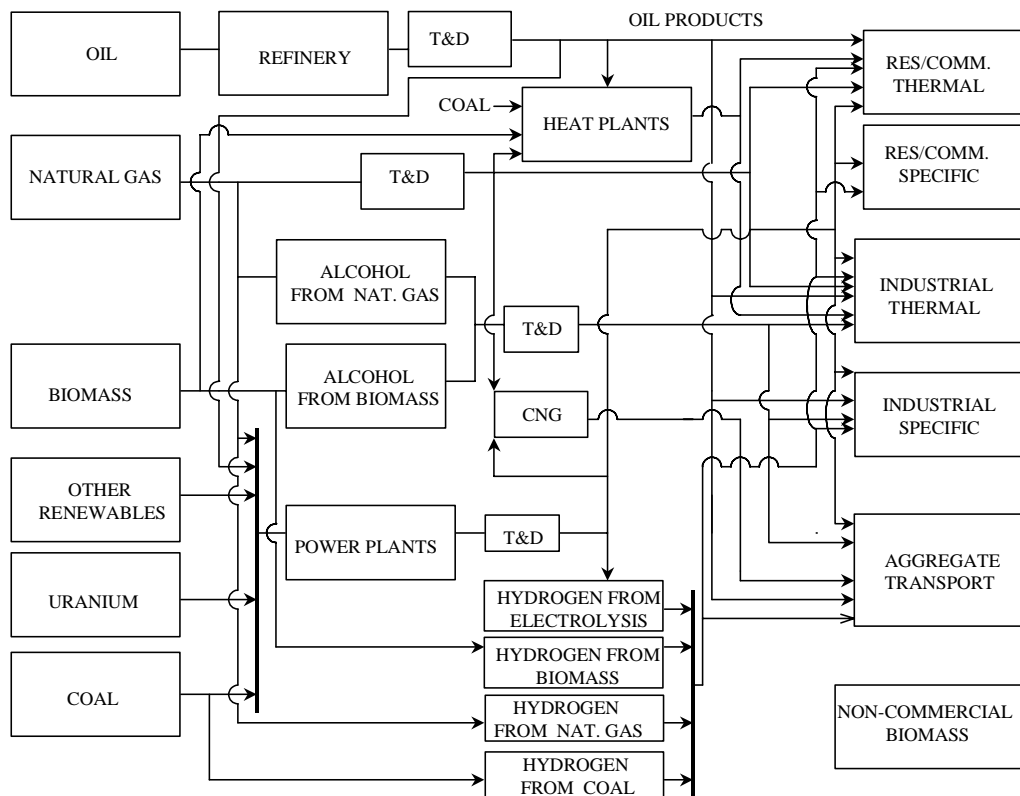


Figure 143. Reference Energy System.

Two technologies are considered for the production of alcohols: Methanol from natural gas and ethanol from wood. However, as a simplification, ethanol and methanol were not differentiated at the final level. A single "alcohol" energy carrier was considered instead. Also, a simplified representation of the refinery was introduced. Two single-input-single-output processes, one for light oil and other for heavy oil products, are considered¹⁰¹.

For the sake of comparability, the characteristics of the electricity production plants have been kept the same as in the analyses presented in chapter 6 and were not taken from the IIASA database. An illustrative sample of the characteristics of some other technologies is shown in Table 19.

¹⁰¹ Although streamlined, such representation is sufficient for the generic model applied here, allowing the required flexibility in the production of the necessary amounts of each fuel, while avoiding the problem of excess availability of a given product, which appears when a single-input multiple-output process with fixed conversion factors is applied in the model.

	Efficiency (%)		Inv. Cost US\$/GJ		Fixed O&M US\$/GJ	Var. O&M US\$/GJ
	Starting year	2050	Start year	2050		
Hydrogen						
• Nat. Gas						
• Coal	0.68	0.68	16	16	1.0	0.46
• Biomass	0.40	0.60	22	19	0.48	0.1
• Electrolysis	0.60	0.70	31.20	21	0.85	1.09
	0.62	0.76	34	21	1.00	0.86
Alcohol						
• Nat. Gas	0.60	0.71	18.3	14.1	0.65	0.55
• Biomass	0.41	0.61	33.3	22.5	2.54	1.48
District Heat						
• Nat. Gas						
• Coal	0.90	0.95	3.0	3.0	0.67	-
• Oil	0.85	0.90	8.7	8.7	0.48	-
• Biomass	0.90	0.95	4.9	4.9	0.92	-
	0.83	0.88	8.7	8.7	0.92	-

Table 19. *Technical characteristics of some selected technologies.*

Standard and advanced generic end-use devices are specified in the different demand categories. Table 20 presents a list of the technologies applied. No explicit investment or O&M costs are considered for the generic end-use technologies specified in the model. However, in lieu of these costs the so-called inconvenience costs are introduced to reflect the fact that as the historical trend of shifting towards more flexible and clean energy carriers continues at the final energy level, some technologies may be more difficult, or much less attractive, to introduce. Thus, substitution at this level is driven mainly by efficiencies and fuel costs. The scenario assumes that the historical shift from non-commercial to commercial fuels and towards more clean and flexible, grid transported energy carriers at the final energy level continues in the future.

As for the non-energy feedstocks, which are mainly oil products and to a much lower extent natural gas and coal, it is considered that they can be replaced by alcohol feedstocks after 2020.

Conservation measures were not explicitly considered and a detailed consideration of the different more efficient technological options in the end-use sectors is not undertaken here. Thus, the caveat must be stated that the model will very likely underestimate the potential of the demand side in responding to an emission constraint, which can be significant. Additional work is necessary in the future to improve such aspects.

Res./Comm. Thermal	Res./Comm. Specific	Industrial Thermal	Industrial Specific	Transportation
<ul style="list-style-type: none"> • Coal heating • Oil heating • Gas heating • Electric heating • Biomass heating • District heating • Methanol heating • Hydrogen heating • Electric heat pump • Gas heat pump • Hydrogen fuel cell (Cogen) • Solar thermal 	<ul style="list-style-type: none"> • Electric appliances • Hydrogen fuel cell 	<ul style="list-style-type: none"> • Coal thermal • Oil thermal • Gas thermal • Electric thermal • Biomass thermal • Process Heat • Methanol thermal • Hydrogen thermal • Electric heat pump • Gas heat pump • Hydrogen fuel cell (Cogen) • Solar thermal 	<ul style="list-style-type: none"> • Electric Specific • Diesel Specific • Hydrogen replacement for Diesel • Methanol replacement for Diesel • Hydrogen Fuel Cell 	<ul style="list-style-type: none"> • Coal based trans. • Oil based trans. • Gas based trans. • Electric-based trans. • Alcohol based trans. • Alcohol fuel cell • Hydrogen fuel cell

Table 20. *Generic end-use technologies applied in the model*

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Curriculum Vitae

Personal data

Name: Tirso Leonardo Barreto Gómez
Place of Birth: Bogotá D.C., Colombia
Date of Birth: 24. 02. 1971
Marital Status: Single

Education

1993-1995: MSc in Electrical Engineering. National University of Colombia
1987-1992: BSc in Electrical Engineering. National University of Colombia
1981-1986: High School in Bogotá D.C., Colombia
1977-1980: Primary School in Bogotá D.C., Colombia

Working Experience

1997-2001: Research Assistant. Energy Modelling Group. General Energy Research Department. Paul Scherrer Institute. Switzerland
1996-1997: Assistant Instructor and Researcher. Department of Electrical Engineering. National University of Colombia.
1994-1996: Specialised Professional. Electricity Systems Planning. Energy and Mining Planning Unit (UPME). Energy Ministry of Colombia.
1993-1994: Graduated Research Assistant. Research Program on Acquisition and Analysis of Electromagnetic Signals (PAAS). Department of Electrical Engineering. National University of Colombia.

