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Extensions to the Energy-System GMM Model: An Overview

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1. Introduction

This report describes recent extensions to the energy-systems GMM (Global Multi-regional MARKAL) model undertaken by the Energy Economics Group (EEG) of the Paul Scherrer Institute (PSI) in Switzerland (hereon referred to as PSI-EEG) in the context of the SAPIENTIA project[1] sponsored by the European Commission (DG Research) and the Swiss National Centre for Competence in Research on Climate (NCCR-Climate).

GMM is a multi-regional "bottom-up" energy-systems optimization model that endogenizes technology learning (Barreto, 2001; Barreto and Kypreos, 2004a; Rafaj *et al.*, 2005, 2006; Rafaj and Kypreos, 2006). The model has been developed and is used at PSI-EEG. The main extensions undertaken here concern the incorporation of a clusters approach to technology learning, the introduction of an improved representation of the transportation sector with emphasis on the passenger sub-sector and the implementation of marginal abatement curves for CH_4 and N_2O, two main non-CO_2 greenhouse gases. Also, a linear representation of the atmospheric concentration of CO_2, CH_4 and N_2O has been included. Other changes are related to the inclusion of additional technologies for production of synthetic fuels (hydrogen and Fischer-Tropsch liquids) and the inclusion of CO_2 capture in fossil-based and biomass-based hydrogen production. Several of the developments described here follow the work of Turton and Barreto (2004, 2006) for the ERIS model at the Environmentally Compatible Energy Strategies (ECS) Program of IIASA.

The remainder of this report is organized as follows. Section 2 describes the basic structure of the GMM model, the main assumptions for the scenario developed and the basic approach to endogenize technology learning in the model and examine the effects of R&D and D&D programs. Section 3 discusses the implementation of technology clusters and describes the key components chosen here. Section 4 presents the improvements to the transportation sector with emphasis on the passenger car sub-sector. Section 5 briefly describes the new technologies for synthetic fuel production and CO_2 capture considered in the model. Section 6 presents the introduction of marginal abatement curves for two main non-CO_2 greenhouse gases, CH_4 and N_2O. Section 7 describes the incorporation of a linearized representation of the atmospheric concentration of CO_2, CH_4 and N_2O. Finally, section 8 summarizes the developments.

2. The Energy-Systems GMM model

2.1. Model Structure

The Global, Multi-regional MARKAL model (GMM) is a "bottom-up" energy-systems model that provides a relatively detailed representation of energy supply

[1] SAPIENTIA stands for Systems Analysis for Progress and Innovation in Energy Technologies for Integrated Assessment. The SAPIENTIA project sponsored by the European Commission (DG Research) is devoted to the assessment of the impacts of energy-related research and development (R&D) activities and demonstration and deployment (D&D) programs on sustainability indicators in the areas of climate change, security of energy supply and transportation, among others.

technologies and a stylized representation of end-use technologies (Barreto, 2001; Barreto and Kypreos, 2004a; Rafaj *et al.*, 2005, 2006; Rafaj and Kypreos, 2006). The GMM model, developed and applied at PSI-EEG, is part of the MARKAL family of models (Fishbone and Abilock, 1981; Loulou *et al.*, 2004), a group of perfect-foresight, optimization energy-system models that represent current and potential future technology alternatives through the so-called Reference Energy System (RES). This kind of models is typically used to obtain the least-cost energy system configuration for a given time horizon under a set of assumptions about end-use demands, technologies and resource potentials. Figure 1 presents a simplified version of the reference energy system (RES) used in all regions in the GMM model.

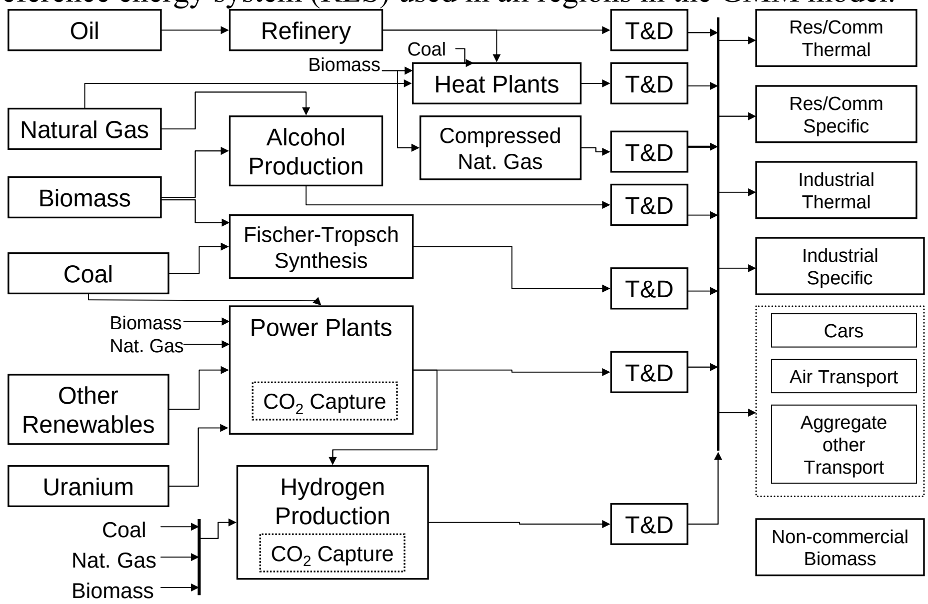

Figure 1: Reference energy system (RES) used in the energy-systems GMM model

The original version of the GMM model was developed by Barreto (2001) and was used to examine the role of emissions trading under the presence of spillovers of technology learning (Barreto and Kypreos, 2004a). The model was revised by Rafaj (2005) and used in several analyses in the context of the examination of the impact of alternative policy instruments on energy-technology strategies and the analysis of synergies and trade-offs between climate policy and other policy domains (Rafaj *et al.*, 2005, 2006; Rafaj and Kypreos, 2006) in the context of the EC-sponsored ACROPOLIS and CASCADE-MINTS projects. Recently, the model was also used to examine the role of hydrogen-fueled fuel cell vehicles in the global passenger car sector (Krzyzanowski, 2006; Krzyzanowski *et al.*, 2006).

The GMM model comprises five regions. Two regions portray the industrialized world, North America (NAM) and the rest of the OECD countries in the year 1990 (OOECD). One region comprises the economies-in-transition in Eastern Europe and the Former Soviet Union (EEFSU). Two additional regions represent the developing world. The first of them brings together developing countries in Asia (ASIA) and the second region groups Latin America, Africa and the Middle East (LAFM). The model has been calibrated to year-2000 energy statistics (IEA, 2002a,b) and the time horizon is 2000 to 2050 with ten-year time periods. Unless specified otherwise, a discount rate of 5% per annum is used in all calculations.

Assumptions about energy resources and demands for energy services have been taken from the B2 scenario quantified with the MESSAGE model (Riahi and Roehrl, 2000) for the IPCC Special Report on Emission Scenarios (SRES, 2000). The B2 scenario constitutes a “middle-of-the road” development where economic growth, population and other driving forces evolve gradually and in a consistent way with historical trends. However, our PSI-EEG baseline scenario cannot be considered to be consistent with the B2 storyline of SRES (2000), which is a source of some of the assumptions in the GMM model. Among other factors, technology dynamics, time horizon, regional disaggregation, etc, in the GMM model differ from those in the MESSAGE-B2 scenario.

2.2. Technology learning in the GMM model

The endogenization of technology learning represents an advance in the representation of technological change in energy optimization models, capturing the early investments (i.e. early accumulation of experience and/or R&D knowledge stock) required for a technology to progress and achieve long-term cost competitiveness (Messner, 1997; Nakićenović, 1997). More importantly, it constitutes a key building block of the “causal chain” from R&D and D&D to sustainability indicators, since it makes an important aspect of technological change (i.e. cost development) dependent upon R&D and D&D policy interventions.

The GMM model endogenizes learning, or experience, curves, where cumulative installed capacity is used as a proxy for accumulated experience (Barreto, 2001; Barreto and Kypreos, 2004a). In a typical one-factor learning curve, the specific investment cost (SC) of a learning technology teat the time period t is formulated as follows:

$$SC_{te,t}(CC) = a * CC_{te.t}^{\ -b} \quad (1)$$

Where:

CC: Cumulative capacity
b: Learning index
a: Specific cost at unit cumulative capacity

Usually, instead of the learning index b, the learning rate (LR), i.e. the rate at which the cost declines each time the cumulative production doubles, is specified. The learning rate can be expressed as:

$$LR = 1 - 2^{-b} \quad (2)$$

Also, and in order to avoid unrealistic and over-optimistic reductions in the investment costs of a particular key component, a “floor” cost, i.e. a lower bound for the specific investment costs is specified.

For the 1FLC representation, a piece-wise linear approximation of the learning curve is implemented through Mixed Integer Programming (MIP) techniques. Box 1 presents a summary of this MIP formulation. For a more detailed description of the MIP approach in the GMM model see Barreto (2001).

Box 1: Description of the Mixed Integer Programming approach to endogenize technology learning in the GMM model (Barreto, 2001).

- The cumulative capacity of a given technology te in the period t is defined as:

$$CC_{te,t} = CC_{te,0} + \sum_{\tau=1}^{t} INV_{te,\tau} \qquad \text{te} \in \{1,\ldots\ldots\text{TE}\},\ \text{t} \in \{1,\ldots\ldots\text{T}\} \ (3)$$

  The parameter $C_{te,0}$ is the initial cumulative capacity (the corresponding cumulative cost $TC_{te,0}$ is also defined). The variable $INV_{te,t}$ represents the investments made on this technology in a particular period t.
- The cumulative capacity is expressed as a summation of continuous lambda variables.

$$CC_{te,t} = \sum_{i=1}^{N} \lambda_{te,i,t} \ (4)$$

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

$$TC_{te,t} = \sum_{i=1}^{N} \alpha_{i,te} * \delta_{te,i,t} + \beta_{i,te} * \lambda_{te,i,t}\ , \qquad \delta_{te,i,t} \in \{0,1\} \ (5)$$

  With: $\beta_{i,te} = \dfrac{TC_{i,te} - TC_{i-1,te}}{CC_{i,te} - CC_{i-1,te}}$ and $\alpha_{i,te} = TC_{i-1,te} - \beta_{i,te} CC_{i-1,te}$ (6)
- The logical conditions to control the active segment of the cumulative curve are:

$$\lambda_{te,i,t} \geq CC_{i,te} * \delta_{te,i,t}, \qquad \lambda_{te,i,t} \leq CC_{i+1,te} * \delta_{te,i,t} \ (7)$$

- The sum of delta binary variables is forced to one:

$$\sum_{i=1}^{N} \delta_{te,i,t} = 1 \ (8)$$

- Using the fact that experience must grow or at least remain at the same level, additional constraints are added to the basic formulation, helping to reduce the solution time. For t=1,…….T, te=1, …..TE, i=1,……N

$$\sum_{P=1}^{i} \delta_{te,P,t} \geq \sum_{P=1}^{i} \delta_{te,P,t+1} \quad , \quad \sum_{P=i}^{N} \delta_{te,P,t} \leq \sum_{P=i}^{N} \delta_{te,P,t+1} \ (9)$$

- The investment cost $IC_{te,t}$ associated to the investments in learning technologies is computed as:

$$IC_{te,t} = TC_{te,t} - TC_{te,t-1} \ (10)$$

  The discounted investment cost is included in the objective function.

It is important to bear in mind the way the learning mechanism operates in a perfect-foresight optimization model like GMM. Due to the underlying increasing returns mechanism, the model tends to act in an "all-or-nothing" manner. If enough learning potential is at hand (depending on the learning rate, the starting point of the learning curve, maximum market penetration rates, potentials etc. specified in the model), the model may choose to introduce the technology as much as possible. But, if the learning potential is not sufficient to render it cost-effective, the technology will very likely remain "locked out" or left only with a marginal contribution.

2.3. Research and Development (R&D) shocks

R&D and demonstration and deployment (D&D) can be thought of as two learning mechanisms that act as complementary channels for knowledge and experience accumulation. Their impacts on sustainability indicators are examined using so-called R&D and D&D "shocks". That is, we examine the change on indicators computed with the modeling system due to a small one-time increment in the R&D knowledge stock or cumulative capacity of a given key learning component.

The so-called two-factor learning curves (hereon referred to as 2FLC) attempt combining the effects of R&D and D&D on technology learning (Kouvaritakis *et al.*, 2000; Barreto and Kypreos, 2004b). In 2FLC, cumulative capacity is used to represent market experience (learning-by-doing) and a knowledge stock function is used to represent the knowledge accumulated through R&D activities (so-called learning-by-searching), respectively (Watanabe, 1995, 1999). The two-factor learning curve for the specific investment costs of a given technology te in the time period t is typically expressed as:

$$SC_{te,t} = a'^{*}KS_{te,t}{}^{-\gamma} * CC_{te,t}{}^{-\sigma} \quad (11)$$

Where:

$CC_{te,t}$: Cumulative capacity
$KS_{te,t}$: Knowledge stock
σ: Learning-by-doing index
γ: Learning-by-searching index
a´: Specific cost at unit cumulative capacity and unit knowledge stock

However, incorporating the 2FLC formulation in an optimization model such as GMM results in a non-linear (NLP), non-convex program (Barreto and Kypreos, 2004b). For such problems, conventional NLP solvers are able to find only locally optimal solutions and global optimization algorithms are suitable only for very small scale problems (Manne and Barreto, 2004). The current size and complexity of the GMM model precludes an efficient solution to the 2FLC non-linear program.

Thus, in order to examine the impact of R&D shocks on a key learning component, we have resorted to an approximation outlined in Turton and Barreto (2004). Instead of the 2FLC formulation, a modified form of the 1FLC MIP formulation of the GMM model is used, where the parameters *a* and *b* are modified to take into account the effect of R&D activities. In this modified formulation, the parameter a in the 1FLC formulation given in equation 1 above is set to:

$$a = a'^{*}KS_{te,t}{}^{-\gamma} \quad (12)$$

In addition, the parameter b is set to σ. That is, it is derived from the 2FLC specification in equation 11.

In doing so, a R&D shock that increases the knowledge stock (KS) brings a reduction in the parameter *a*. If the knowledge stock remains constant thereafter, then *a* remains constant as well. Accordingly, an R&D shock can be incorporated into the single-factor learning formulation by varying *a* according to Equation 12. This procedure is described in more detail in Turton and Barreto (2004). It should be noticed that this approximation does not allow the model to invest on R&D after the shock.

2.4. Demonstration and deployment (D&D) shocks

Demonstration and Deployment (D&D) shocks are simulated as an exogenous investment in a particular technology that leads to the installation of additional capacity. In order to ensure comparability with the R&D shocks described above, it has been assumed that D&D (capacity) shocks affect a single learning component, rather than an entire technology comprising a number of learning and non-learning components. In reality, however, a D&D program would not consist in the deployment of a single component but of a full technology.

Figure 2 presents a simplified scheme that illustrates the respective effects of R&D and D&D shocks in the 1FLC formulation used here. Essentially, an R&D shock will shift the starting point of the learning curve downwards. That is, it will reduce the specific investment cost of the key learning component but will not increase the cumulative capacity. On the other hand, a D&D shock will let the key component move down the learning curve, i.e. by increasing the installed cumulative capacity it will reduce the corresponding specific investment costs.

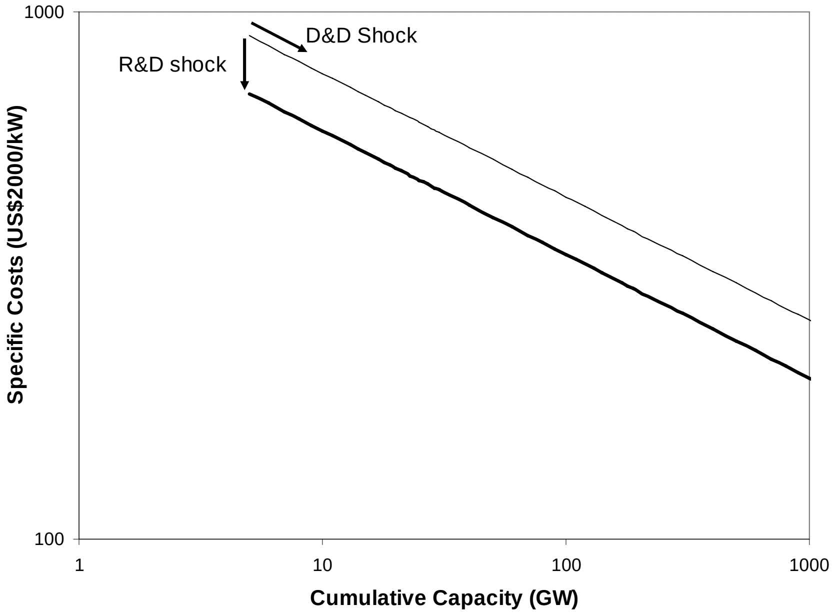

Figure 2: Schematic effect of the Research and Development (R&D) and Demonstration and Deployment (D&D) shocks with the 1FLC formulation used in the GMM model.

3. A Clusters Approach to Technology Learning

Technologies do not evolve in isolation. Development and adoption of technologies occur as collective evolutionary processes (Silverberg, 1991). Complex interactions where several technologies reinforce and cross-enhance each other drive to the creation of technology clusters (Sahal, 1980), i.e. families of technologies evolving and diffusing together, and to the constitution of associated networks of economic and social actors. Clusters play an important role in technological change. Historically, certain clusters have evolved to become dominant, driving to the conformation of technological regimes (Nakićenović, 1997; Grübler *et al.*, 1999). Technological regimes are difficult to replace because compatible changes are attracted and incorporated by the existing regime while incompatible (radical) changes are discouraged. As a consequence, clusters tend to exhibit a self-reinforcing behavior.

The technologies that constitute a given cluster are related by multiple links that contribute to magnify their economic, social and environmental impacts. These multiple relations contribute to make progress in one of them relevant, directly or indirectly, to other members of the cluster, while contributing to reinforce their own position in the marketplace. Learning spillovers from one technology may trigger improvements in related technologies. Also, performance/cost advances in a particular technology can make a whole energy chain more attractive than others.

It is important to study how technology clusters emerge and evolve, in order to gain insights into the actions that are necessary to promote the introduction of clusters of environmentally sound energy supply and end-use technologies. Therefore, it is necessary to develop an adequate representation of the mechanisms that account for mutual influences between technologies in energy-systems models.

One of those mechanisms is technology learning, i.e. the improvement in cost/performance of technologies as a result of market experience and/or R&D activities. Technological "proximity" may stimulate a collective learning process. Seebregts *et al*. (2000) have applied the "key technology" concept to the representation of technology learning in "bottom-up" energy system models. This approach allows 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 (i.e. the key technology). Gritsevskyi and Nakićenović (2000) have also introduced clusters of technologies, defined according to their technological "proximity", considering learning spillovers both within and between different clusters.

Here, following the "key technology" approach implemented by Seebregts *et al*. (2000) for the European MARKAL model and Turton and Barreto (2004) for the ERIS model, key components have been introduced in the GMM model in the areas of electricity generation, synthetic fuel production (alcohols and hydrogen), CO_2 capture in fossil and biomass-based power plants and hydrogen production as well as in passenger transportation technologies (cars and buses). Besides providing a mechanism to capture interactions between related technologies as described above, the clusters approach allows extending the number of technologies in which learning takes place while keeping the computational complexity at a reasonable level.

In the clusters approach implemented here, it is assumed that there are full spillovers between technologies belonging to the same cluster. Also, it has been assumed that technology learning takes place at the global scale. Thus, the relationship between the cumulative capacity of a given key component kc and the cumulative capacity of the technologies te that share the component in the time period t is as follows:

$$CCAP_{kc,t} = \sum_{tetokc} \sum_{reg} clust_{tetokc} * CCAP_{te,t} \quad (13)$$

Where:
$CCAP_{kc,t}$: Cumulative capacity of key component kc in time t
$CCAP_{tech,t}$: Cumulative capacity of technology te in time t
tetokc: Mapping set between key component kc and technologies te sharing it
$clust_{tetokc}$: Clustering factor relating the fraction of cumulative capacity of technology te that contributes to cumulative capacity of the key component kc

Learning curves are implemented only for investment costs of the key components. For all the key components, a so-called "floor cost", i.e. a minimum cost level at which the learning process ceases, has been introduced in order to avoid unrealistic cost reductions.

The key components represented in the GMM model (and the corresponding abbreviations used to identify them) are as follows:

- Gasifier (GSF)
- Stationary fuel cell (SFC)
- Mobile fuel cell (MFC)
- Gas turbine (GTU)
- Solar photo-voltaics(SPV)
- Wind turbine (WND)
- Advanced nuclear power plant (Generation III+, IV) (NNU)
- Battery (BAT)
- Stationary steam methane reformer (SRR)
- Mobile auto-thermal reformer (MRR)
- Biomass-to-ethanol via the "sugar" process (BET)
- CO_2 capture in conventional coal power plants (post-combustion) (CC1)
- CO_2 capture in natural gas combined-cycle power plants (post-combustion) (CC2)
- CO_2 capture in coal and biomass-based integrated gasification combined-cycle (IGCC) power plants (pre-combustion) (CC3)
- CO_2 capture in hydrogen production (natural gas steam reforming/coal gasification/biomas gasification) (CC4)

Table 1 presents the relationship between key components and technologies under consideration in the GMM model. Altogether, these 15 key components are related to about 30 energy supply and end-use technologies. Learning curves are implemented only for investment costs of the key components, which are measured in US dollars of the year 2000 per kW installed (US$2000/kW). The corresponding measure of experience is cumulative capacity, measured in GigaWatts (GW, i.e. 10^9 Watt). For all the key components, a so-called "floor cost", i.e. a minimum cost level at which the learning process ceases, has been introduced in order to avoid unrealistic cost reductions. Notice that when a R&D or D&D shock is imposed on a key component, all the technologies from which this component makes part will be affected.

Figure 3 presents an example of a cluster of technologies sharing a key learning component. The gasifier (GSF) makes part of coal and biomass-based Integrated

Gasification Combined Cycle power plants (IGCC), coal and biomass-based hydrogen production and coal and biomass-based Fischer-Tropsch synthesis. Notice that, as a simplification, in the GMM model it is assumed that the same gasifier is used in biomass and coal-based technologies. Also, the current diversity of gasifiers has not been considered (Ciferno and Marano, 2002; Yamashita and Barreto, 2004).

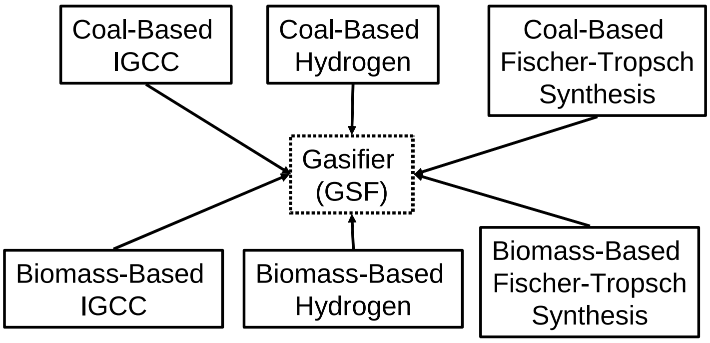

Figure 3: Example of technologies sharing a key learning component. The gasifier (GSF) makes part of coal and biomass-based Integrated Gasification Combined Cycle power plants (IGCC), coal and biomass-based hydrogen production and coal and biomass-based Fischer-Tropsch synthesis.

Figure 4 illustrates the case of one technology having several key learning components. The hydrogen-powered fuel-cell vehicle (FCV) considered here is a fuel-cell-battery hybrid car that comprises two key learning components, namely a mobile fuel cell (MFC) and a battery (BAT). The balance of system (BoS) is assumed to be non-learning.

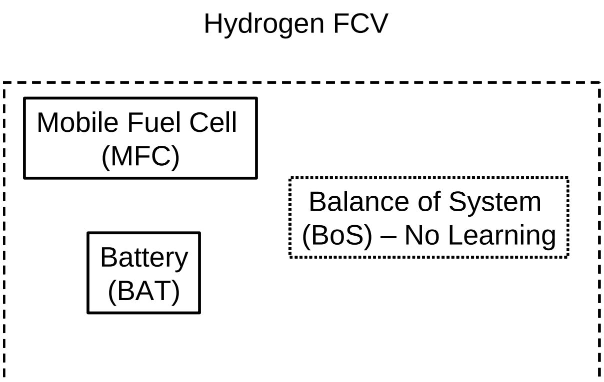

Figure 4: Example of a technology having several key components. The hydrogen-powered fuel-cell vehicle (FCV) considered here is a fuel-cell-battery hybrid car that comprises two key learning components namely a mobile fuel cell (MFC) and a battery (BAT). The balance of system (BoS) is assumed to be non-learning.

Table 1: Relationship between key components and energy technologies in the GMM model

	Key Components														
	GSF	SFC	MFC	GTU	SPV	WND	NNU	BAT	SRR	MRR	BET	CC1	CC2	CC3	CC4
Technology															
Electricity Generation															
Gas turbine				X											
Gas combined cycle				X											
Gas combined cycle+CO_2 capture				X									X		
Coal-based IGCC	X			X											
Coal-based IGCC+CO_2 capture	X			X										X	
Conventional coal power plant+CO_2 capture												X			
Biomass-based IGCC	X			X											
Biomass-based IGCC+CO_2 capture	X			X										X	
Solar PV					X										
Wind turbine						X									
Advanced nuclear power plant							X								
Gas fuel cell		X													
Hydrogen fuel cell		X													
Fuel production															
Natural gas to hydrogen									X						
Natural gas to hydrogen+CO_2 capture									X						X
Natural gas to methanol									X						
Coal gasification to hydrogen	X														
Coal gasification to hydrogen+CO_2 capture	X														X
Coal to Fischer-Tropsch liquids	X														
Biomass gasification to hydrogen	X														
Biomass gasification to hydrogen+CO_2 capture	X														X
Biomass to Fischer-Tropsch liquids	X														
Biomass to ethanol											X				
Passenger cars															
Gasoline hybrid-electric car								X							
CNG hybrid-electric car								X							
Hydrogen hybrid-electric car								X							
Gasoline fuel-cell car			X					X		X					
Methanol fuel-cell car			X					X		X					
Hydrogen fuel-cell car			X					X							

Table 2 to Table 4 present the dissagregation of investment costs for the technologies associated with learning key components, distinguishing the contribution of the associated key components.

Table 2: Disaggregation of investment costs of learning electricity generation technologies in the GMM model. Investment costs are split into those pertaining to the key learning components associated with a given technology and the Balance of System (BoS). Costs are given in US$2000/kW.

	Key Components (US$/kW)										**BoS (US$/ kW)**	**Total (US$/ kW)**
	GSF	SFC	GTU	SPV	WND	NNU	CC1	CC2	CC3	SRR		
Technology												
Gas turbine			200								150	350
Gas combined cycle			200								360	560
Gas combined cycle+CO_2 capture			200					542			360	1102
Coal-based IGCC	300		200								900	1400
Coal-based IGCC+CO_2 capture	300		200						509			1909
Conventional coal power plant+CO_2 capture							940				1150	2090
Biomass-based IGCC	300		200								1000	1500
Biomass-based IGCC+CO_2 capture	300		200						509		1000	2009
Solar PV				5500								5500
Wind turbine					1200							1200
Advanced nuclear power plant						2200						2200
Gas fuel cell		1250								180	1000	2430
Hydrogen fuel cell		1250									1750	3000

Table 3: Disaggregation of investment costs of learning fuel production technologies in the GMM model. Investment costs are split into those pertaining to the key learning components associated with a given technology and the Balance of System (BoS). Costs are given in US$2000/kW.

	Key Components (US$/kW)				**BoS (US$/kW)**	**Total (US$/kW)**
	GSF	SRR	BET	CC4		
Natural gas to hydrogen		180			160	340
Natural gas to hydrogen+CO_2 capture		180		200	160	540
Natural gas to methanol		180			520	700
Coal gasification to hydrogen	300				400	700
Coal gasification to hydrogen+CO_2 capture	300			200	400	900
Coal to Fischer-Tropsch liquids	300				750	1050
Biomass gasification to hydrogen	300				950	1250
Biomass gasification to hydrogen+CO_2 capture	300			200	950	1450
Biomass to Fischer-Tropsch liquids	300				1750	2050
Biomass to ethanol			1380			1380

Table 4 presents the costs of key components, the rest of the drivetrain and the balance of system (BoS) for the passenger car technologies incorporated in the GMM as learning technologies. These technologies include hybrid-electric vehicles (HEV) and fuel-cell vehicles (FCV). The FCV considered here are fuel-cell-battery hybrid vehicles (Ogden *et al.*, 2004). That is, they incorporate both a Proton Exchange Membrane (PEM) fuel cell and a battery. From a clusters point of view, three key learning components play a role in this set of automobile technologies. The battery

(BAT) is the key learning component associated with the hybrid-electric vehicles (HEV). In the case of the fuel-cell vehicles, all of them are associated to both the mobile fuel cell (MFC) and the battery (BAT). In addition, the methanol-based and gasoline-powered FCV are linked to the on-board mobile reformer (MRR).

Table 4: Disaggregation of investment costs of learning passenger car technologies in the GMM model. Investment costs are split into those pertaining to the key learning components associated with a given technology, the rest of the drive-train system and the Balance of system (BoS). Costs for the learning components are given in US$2000/kW. Total costs for the passenger cars are given in US$2000 per car.

	Key Components						**Rest of Drive-Train (US$)**	**BoS (US$)**	**Total (US$)**
	MFC US$/kW	BAT US$/kW	MRR US$/kW	MFC Total (US$)	BAT Total (US$)	MRR Total (US$)			
Hybrid-electric Vehicles (HEV)									
Gasoline hybrid-electric car		40			1420		2918	10000	14338
CNG hybrid-electric car		40			1384		3114	10000	14498
Hydrogen hybrid-electric car		40			1432		4166	10000	15598
Fuel-cell Vehicles (FCV) [(a)]									
Gasoline fuel-cell car	300	40	90	14400	1828	5184	1444	10000	35736
Methanol fuel-cell car	300	40	90	11475	1756	4131	1450	10000	31107
Hydrogen fuel-cell car	300	40	90	9525	1612		2329	10000	25371

Notes:

(a) The fuel-cell vehicles considered here are fuel-cell-battery hybrid vehicles.
(b) The abbreviations for the key learning components are as follows. MFC stands for Mobile Fuel Cell, BAT for battery and MRR for Mobile Reformer.

Clustering factors represent the fraction of installed capacity of a given technology that corresponds to the installed capacity of the learning key component. For example, in a gas combined-cycle power plant, the gas turbine only represents approximately 60% of the total installed capacity. Thus, the clustering factor of the gas combined-cycle turbine in relation to the gas turbine key component is 0.6. That is, the cumulative capacity of the combined-cycle technology weighted by the corresponding clustering factor is the contribution of this technology to the cumulative capacity of the gas turbine. Also, it should be taken into account that the clustering factors may also depend on the units used in the model to measure investments and, therefore, cumulative capacity in a given technology. This is the case for passenger car technologies, where cumulative capacity is measured in vehicle-km, while the cumulative capacity of, for instance, a mobile fuel cell (MFC) or a battery (BAT) key component is measured in kW. In this case, the clustering factors represent a conversion between vehicle-km and kW, according to the installed capacity of each key component per vehicle.

Figure 5 and Figure 6 illustrate the one-factor learning curves (1FLC) assumed in the GMM model.

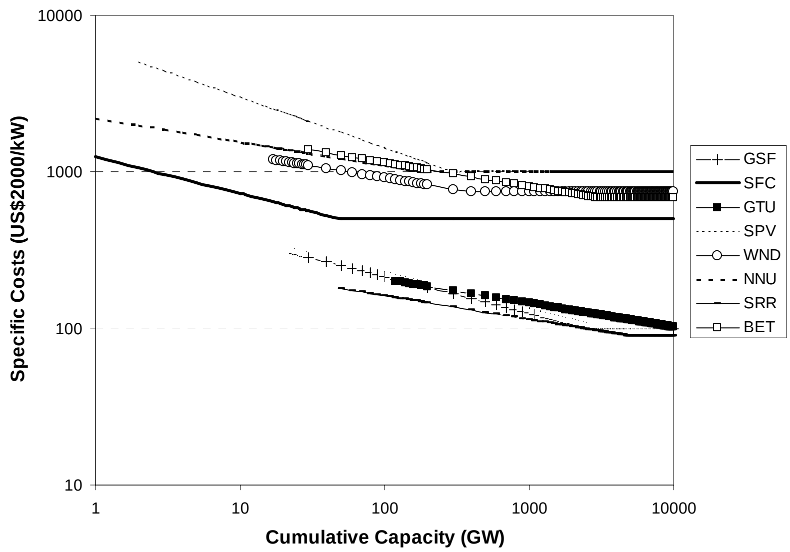

Figure 6: One-factor learning curves assumed for key components in the electricity generation and fuel production sectors in the GMM model

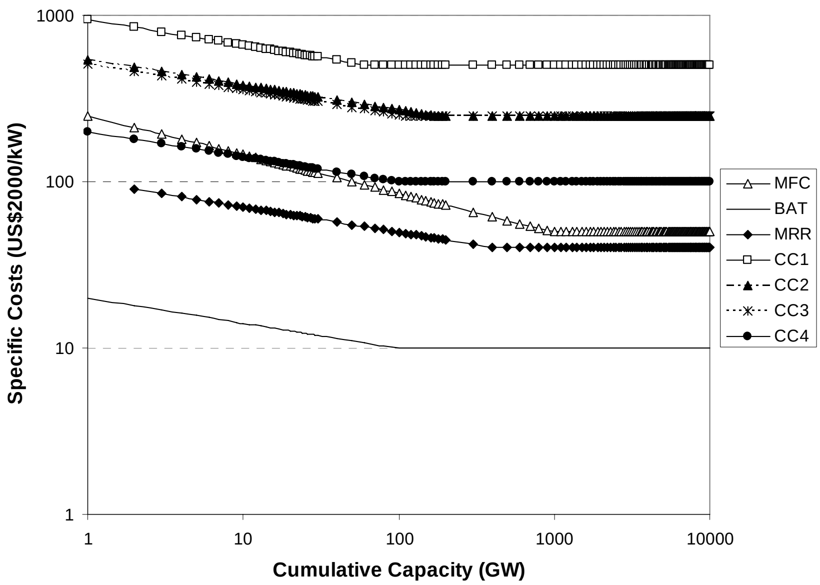

Figure 7: One-factor learning curves assumed for key components in the CO_2 capture and passenger transport sector (cars and buses) in the GMM model

4. Disaggregation of the Transportation Sector

The transportation sector has evolved into a major concern due to its growing energy consumption, its overwhelming reliance on petroleum products and the polluting emissions associated with it. The need to strive towards a sustainable transport system has been widely recognized (IEA, 2003; WBSCD, 2001). Specific attention is required in achieving sustainable mobility in the passenger car sub-sector in the long run, a goal encompassing major technological, economic and social challenges. The transportation sector has been disaggregated and expanded in order to allow the examination of the impact of specific technologies of interest in the passenger car sector, a major concern for policy makers due to its impacts on the environment and on security of energy supply.

The transportation sector in the GMM model was originally conceived as an aggregate sector where generic technologies were used to mimic final-energy use. The new representation divides the transport sector into three sectors, namely passenger cars, air transport and other transport. For the passenger car mode, a relatively detailed technology representation is introduced. In the other two sectors, a simplified representation has been chosen with generic technologies that mimic the final-energy use.

4.1. Passenger cars

The demand projection for passenger car mobility used in this scenario has been developed by basically applying the growth rates for passenger mobility in different world regions provided by the WBCSD (2004) to the year-2000 figures of vehicle-km per region estimated by Turton and Barreto (2004, 2006). An exception is the ASIA region where a growth rate of 4% per annum has been assumed over the whole time horizon. The assumptions about kilometers driven per car and year for each world region are based on the estimates of Schafer (1995, 1998) and WBCSD (2001). The resulting scenario is presented in Figure 8 and shows global passenger car mobility measured in vehicle-km more than doubling between the years 2000 and 2050. The fastest growth occurs in the developing regions (ASIA, LAFM) but a “car mobility divide” between industrialized and developing regions still persists towards the middle of the 21st century.

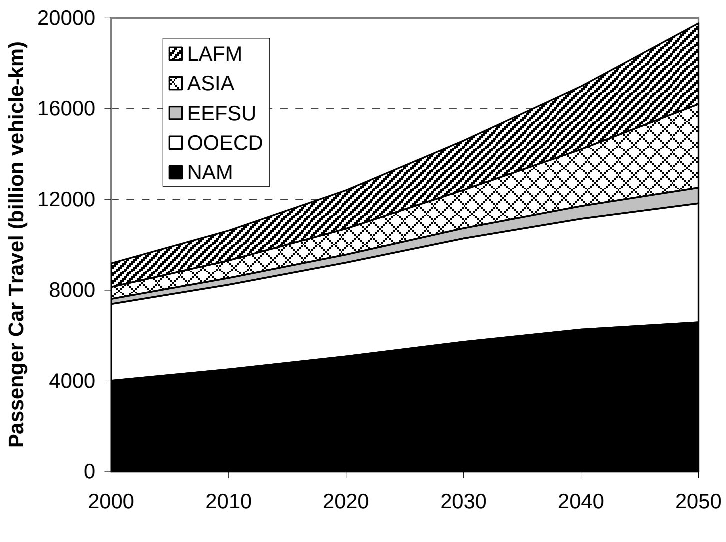

Figure 8: Demand projection for passenger car travel per region in the scenario developed here. The description of the regions can be found in section 2.1 above.

The set of automobile technologies considered in the GMM model is presented in Table 5. As mentioned previously, three main kinds of technologies are incorporated in the database, namely internal combustion engine vehicles (ICEV), hybrid-electric vehicles (HEV) and fuel cell-hybrid vehicles (FCV). The ICEV can be considered as the incumbent, dominant technology which still has some room for improvement. The

HEV represents an advanced evolutionary technology, compatible to a good extent with today's dominant technological regime.[2] The FCV, in this turn, is a revolutionary technology, which would require more radical changes to the current technological regime. For each of these technologies several fuels were considered. The technical and cost characteristics were taken from different sources in the literature (Ogden *et al.*, 2003; Weiss *et al.*, 2003).

Table 5: Main characteristics of automobile technologies in the GMM model

Technology	Fuel Efficiency (v-km/MJ)	Initial Investment Cost (US$2000 per car) [(c)]	Starting Date
Internal Combustion Engine (ICEV)			
Oil products standard ICEV[(b)]	0.21-0.354[(a)]	12425	2000
Oil products advanced ICEV	0.599	12825	2010
CNG standard ICEV	0.19-0.32 [(d)]	12625	2000
Hybrid-electric Vehicles (HEV)			
Oil products HEV	0.761	14338	2010
CNG HEV	0.658	14498	2010
Hydrogen HEV	0.814	15598	2020
Fuel Cell Vehicles (FCV)			
Oil products FCV	0.656	32681	2020
Methanol FCV	0.735	27926	2020
Hydrogen FCV	1.060	25371	2020

Notes:

(a) The fuel efficiency of the standard internal combustion engine is region and time-dependent. It has been assumed that it improves over time and in all world regions reaches the upper figure quoted in the table above towards the end of the time horizon (2050).

(b) As a simplification, no distinction has been made between gasoline and diesel-powered vehicles and this category is referred to as oil-products vehicles. The values assumed here, however, correspond to those of a gasoline-fuelled vehicle.

(c) For the HEV and the FCV technologies, which incorporate learning components as described in section 3, this cost estimate is computed using the initial investment cost of the components. For all technologies considered here it is assumed that the cost of the rest of the car, excluding the drive train, is US$ 10000. In this document this non-learning part is referred to as Balance of System (BoS).

(d) It is assumed that the CNG-fuelled internal combustion engine vehicle is 10% less efficient than its oil-products-based counterpart.

The sizes of the battery for the HEVs and the fuel cell and battery for the FCVs have been taken from Ogden *et al.* (2004) as follows:

Table 6: Size of battery and fuel cell key components (in kW) for hybrid-electric vehicles (HEV) and fuel cell vehicles (FCV) in the GMM model

Technology	Battery Size (kW)	Fuel Cell Size (kW)
Hybrid-electric Vehicles (HEV)		
Oil products HEV	35.5	
CNG HEV	34.6	
Hydrogen HEV	35.8	
Fuel Cell Vehicles (FCV)		
Oil products FCV	45.7	57.6
Methanol FCV	43.9	45.9
Hydrogen FCV	40.3	38.1

[2] For a discussion of the concept of technological regime see Kemp (1997).

4.2. Air transportation

The air transport sector has been modeled at the final-energy level. Demands for the year 2000 have been derived from IEA statistics (IEA, 2002a,b). It is assumed that the air transport demand will grow at the same pace as the GDP growth rates of the SRES-B2 scenario (see Figure 9). This growth, compounded over 50 years, amounts to an approximately 4-fold increase in global final-energy demand for air transport. Most of the growth takes place in the developing regions, which by the year 2050 account for about 50% of the global final-energy consumption in this sector.

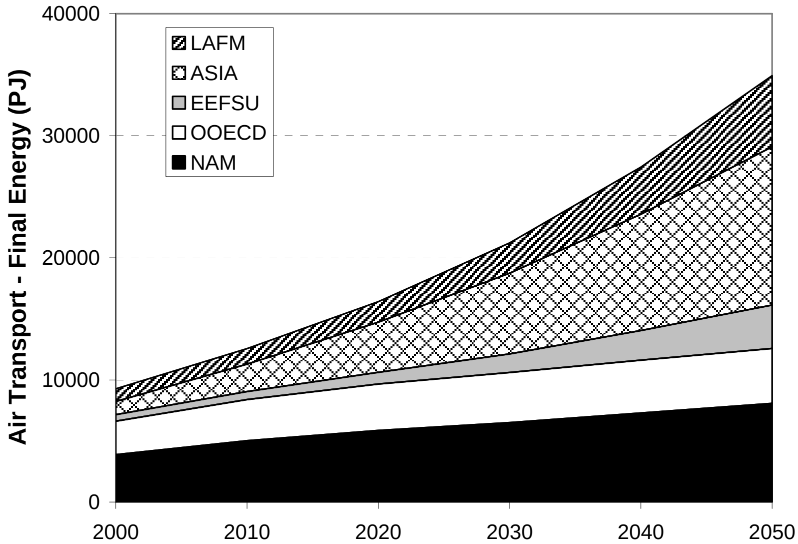

Figure 9: Demand projection for air transport per region in the scenario developed here. The description of the regions can be found in section 2.1 above.

Only two oil-based generic technologies have been considered, under the assumption that other competing technologies, such as hydrogen-powered aircraft would be available only in the second half of the 21^{st} century. The first generic oil-based aircraft technology allows the final energy demand in the air transport sector to grow at the GDP growth rate. The second is a more expensive generic aircraft technology whose fuel efficiency of technology improves over time. The latter allows a decoupling between the growth in final-energy demand in this sector and GDP growth.

4.3. Other transportation

The rest of the transportation sector, comprising mainly freight transport, has been considered as an aggregate sector where generic technologies representing the standard use of different fuels (mainly combustion systems) and two advanced fuel-cell systems mimic the final energy consumption. Demands for the year 2000 have been derived from IEA statistics (IEA 2002a,b). Thereafter, regional final-energy demand for other transport is assumed to grow indexed to the GDP projections of the SRES B2 scenario (Figure 10). Again, most of the growth in this scenario takes place in the developing regions, which together account for about 60% of the global final-energy demand for other transportation towards the end of the first half of the 21st century.

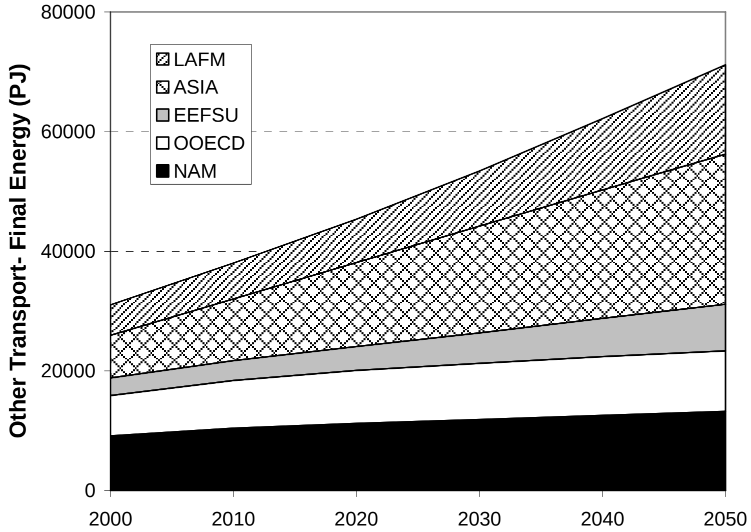

Figure 10: Demand projection for other aggregate transport per region in the scenario developed here. The description of the regions can be found in section 2.1 above.

The generic technologies included in the "other transport" sub-sector in the GMM model are as follows:

- Coal-based other transport
- Oil-based other transport
- Natural gas-based other transport
- Electricity-based other transport
- Alcohol-based other transport
- Methanol fuel-cell other transport
- Hydrogen fuel-cell other transport

5. Additional Technologies

We have included additional technologies for production of synthetic fuels, electricity generation and CO_2 capture in the GMM model. Specifically, given that Fischer-Tropsch (F-T) liquids (specifically F-T diesel) may have a promising potential as transportation fuels in the medium term, production of Fischer-Tropsch liquids (diesel) from coal and biomass has been included (Steiger, 2000; Hamelinck *et al.*, 2003; Yamashita and Barreto, 2004, 2005). Also, biomass gasification with and without CO_2 capture has been considered in addition to biomass combustion power plants already existing in the model's database. CO_2 capture has been introduce for hydrogen production from coal and biomass gasification and steam reforming of natural gas, following several literature sources (Ogden *et al.*, 2004; Simbeck and Chang, 2002; Parsons *et al.*, 2002; David and Herzog, 2001).

6. Incorporation of Marginal Abatement Curves for CH_4 and N_2O

The consideration of non-CO_2 greenhouse gases (GHG) is an important aspect when examining cost-effective strategies for mitigation of global climate change (e.g. Manne and Richels, 2000, 2004; Reilly *et al.*, 1999, 2003). Although CO_2 is the most significant contributor to climate change, other GHGs play also an important role, in particular due to the fact that they are associated with a much more potent greenhouse effect in the atmosphere than CO_2. Including non-CO_2 GHGs may have noticeable effects on the costs and composition of mitigation strategies. Thus, they represent an important component when it comes to enhance the degree of flexibility of climate-change mitigation strategies.

There are several possibilities for considering the effects of non-CO_2 GHG abatement in a "bottom-up" modeling framework. One of them is the explicit inclusion of abatement technologies, an approach that has been followed by Rao and Riahi (2004) and Delhotal *et al.*, (2004), among others. The second approach is the use of aggregate marginal abatement curves, built on the basis of assessment of abatement technologies.

In this section, a brief description of the approach for incorporating marginal abatement curves in the GMM model is presented. Following the work of Manne and Richels (2000, 2004) for the MERGE model and Turton and Barreto (2004) for the ERIS model, we incorporate marginal abatement curves (MACs) for the two main non-CO_2 greenhouse gases, namely methane (CH_4) and nitrous oxide (N_2O), considering both energy-related and non-energy-related sources. This approach uses the regional marginal abatement curves for non-CO_2 GHGs estimated by U.S EPA (2003). By incorporating MACs for these non-CO_2 GHGs, the context for the examination of energy-technology strategies in the GMM model is substantially improved. The appendix A1 describes the GMM implementation in detail.

6.1. Definition of baseline emissions

Following US EPA (2003), the categories considered in this analysis are as follows: CH_4 emissions from coal, oil and gas production, solid waste management and manure management, N_2O emissions from adipic and nitric acid production. Baseline emissions must be defined for these different sources of emissions. Baseline emissions can be endogenous if they are linked to a model variable or exogenous if they are specified from sources external to the model. In this formulation, energy-related methane emissions from coal, oil and gas production are endogenous to the model. Emissions from other sources are exogenous to the model.

Other sources of CH_4 (enteric fermentation and rice paddies) and N_2O (soils) emissions are also considered exogenously. However, since no MACs are specified for them in the US EPA study (2003), they are treated here as non-abatable emissions. It must be noticed that these sources of emissions currently represent a large fraction of the total emissions of these non-CO_2 gases worldwide (Reilly *et al.*, 2003), but, uncertainties still abound regarding the potential, costs and feasibility of implementation of those measures.

6.2. Definition of marginal abatement curves

The marginal abatement curves (MACs) are given to the model as stepwise curves relating abatement costs and abatement potentials. These abatement potentials are given either as absolute potentials, e.g. in tons of the respective GHG or carbon-equivalent, or in relative terms (e.g. percentage) of a given baseline. In what follows, it is assumed that the abatement potentials are given as a fraction of the baseline and that emissions from non-CO_2 GHG are expressed in terms of carbon-equivalent (C-eq) emissions using the 100-years global warming potentials (GWP) reported by IPCC (2001), namely 21 for CH_4 and 310 for N_20.[3] Correspondingly, abatement costs are given in US$/ton C-eq.

The abatement potentials have been derived on the basis of considerations of availability, reduction efficiency and technical and economic applicability of the different abatement options (Delhotal *et al*., 2003). Abatement potentials per price step, region, and GHG are specified for a reference time period, here chosen as 2010. We did not consider no-regrets options in this specification. That is, all MACs were shifted upwards such that abatement costs are always positive. Abatement potentials for other periods are computed using the so-called technical-progress multipliers (tm). These multipliers represent the fact that abatement technologies may improve over time, thus increasing the abatement potential achievable at a given cost. The multipliers allow extrapolating the MACs beyond 2010, the reference year.

It has to be recognized that these multipliers provide only a rudimentary way to represent technical change in non-CO_2 abatement options and that this takes place only exogenously (i.e. it does not depend on the amount of cumulative abatement). Moreover, at this point their choice is somewhat arbitrary and dependent on the modeler's judgment. Delhotal *et al.* (2003) have proposed a methodology for shifting MACs into the future on the basis of technology assessment for individual technologies, but figures are not yet available for multiple regions and/or sectors.

[3] The use of global warming potentials (GWP) has been criticized in the literature because they do not constitute an adequate "exchange rate" between GHGs (O'Neill, 2000; Manne and Richels, 2000; Fuglestvedt *et al.,* 2003). Specifically, they fail to capture a number of physical and chemical interactions between GHGs and differences in their persistence in the atmosphere, among others. Also, they lack an economic rationale. However, the use of alternative, economic indices proposed in the literature, which rely mostly on the monetization of damages due to climate change, has not been possible so far given the huge uncertainties that currently surround the assessment of climate damages (Reilly *et al.*, 2003).

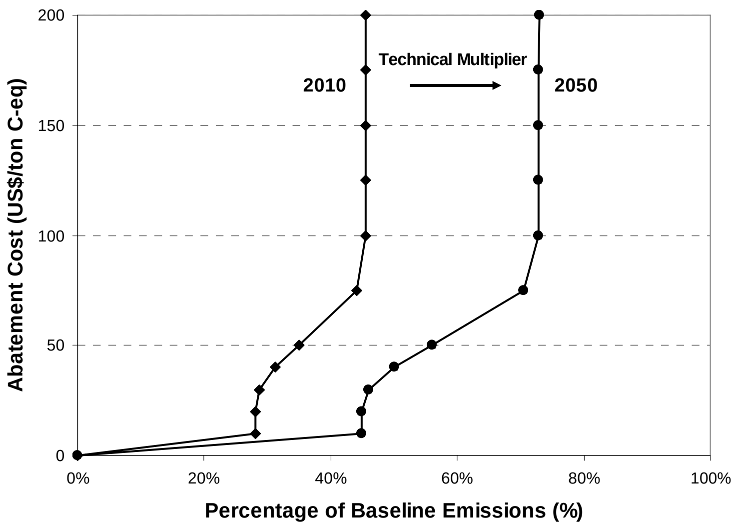

Figure 11: Illustration of the effect of technical multipliers to shift marginal abatement curves out into future periods.

6.3. Computation of abatement and remaining emissions

In what follows, we describe the basic equations of the MAC formulation in the GMM model. The following notation is used here for sets, parameters and variables:

Sets

GHG:	GHG emissions category
ERGHG:	Energy-related GHG emissions (a subset of GHG)
NERGHG:	Non-energy-related GHG emissions (a subset of GHG)
MSTEP:	Step of the MAC
REG:	Region
TP:	Time period

Parameters

$abtpref_{GHG,REG,TP}$:	Abatement potential for the reference period (percentage)
$abatepot_{GHG,REG,TP}$:	Abatement potential for other periods (percentage)
$bline_{NERHG,REG,TP}$:	Exogenous baseline emissions for non-energy-related GHGs
$tm_{GHG,REG,TP}$:	Technical multipliers
$gr_{GHG,REG,TP}$:	Growth rate
Δt:	Period length
GWP_{GHG}:	Global Warming Potential of a given GHG

Variables

$EMGHG_{GHG,REG,TP}$:	GHG emissions per GHG category, region and time period
$EREM_{ERGHG,REG,TP}$:	Baseline energy-related GHG emissions per ERGHG category, region and time period
$ABATE_{GHG,REG,TP}$:	Abatement per GHG category, region and time period
$CEQEM_{REG,TP}$:	Carbon-equivalent emissions (CO_2+CH_4+N_2O)

The abatement potentials for time periods beyond the reference period (in our case 2010) are defined as the abatement potential for the reference period multiplied by the corresponding technical-progress multipliers:

$$abatepot_{GHG,REG,TP} = tm_{GHG,REG,TP} * abtpref_{GHG,REG,TP} \quad (14)$$

The baseline energy-related emissions ($EREM_{ERGHG,REG,TP}$) are computed as a function of the related activity variables in the model (in this case CH4 emissions from coal, oil and gas production). Notice that the corresponding emission coefficients may be reduced over time if, for instance, a reduction of leakage in pipelines is assumed.

The amount of abatement per period, region and sector is constrained to (for energy-related and non-energy-related emissions respectively):

$$ABATE_{ERGHG,MSTEP,REG,TP} \leq abatepot_{ERGHG,MSTEP,REG,TP} * EREM_{ERGHG,REG,TP} \quad (15)$$

$$ABATE_{NERGHG,MSTEP,REG,TP} \leq abatepot_{NERGHG,MSTEP,REG,TP} * bline_{NERGHG,REG,TP} \quad (16)$$

The resulting energy-related emissions are computed as the endogenous baseline emissions minus the corresponding abatement as follows:

$$EMGHG_{ERGHG,REG,TP} = EREM_{ERGHG,REG,TP} - \sum_{MSTEP} ABATE_{ERGHG,MSTEP,REG,TP} \quad (17)$$

Similarly, the resulting non-energy-related emissions are computed as the exogenous baseline emissions minus the corresponding abatement:

$$EMGHG_{NERGHG,REG,TP} = bline_{NERGHG,REG,TP} - \sum_{MSTEP} ABATE_{NERGHG,MSTEP,REG,TP} \quad (18)$$

The carbon-equivalent (C-eq) emissions are computed as:

$$CEQEM_{REG,TP} = \sum_{GHG} GWP_{GHG} * EMGHG_{GHG,REG,TP} \quad (19)$$

In order to avoid abrupt changes in non-CO_2 emissions as a result of cost-effective abatement, we have introduced a maximum growth constraint for the abatement of non- CO_2 GHGs. This constraint also reflects the fact that, in reality, abatement technologies will experience a diffusion process that takes time and, thus, their abatement potential cannot be tapped fully at once.

$$\sum_{MSTEP} ABATE_{GHG,REG,TP} \leq \left[\sum_{MSTEP} ABATE_{GHG,REG,TP-1} \right] * (1+gr)^{\Delta t} \quad (20)$$

7. Concentration of Greenhouse Gases in the GMM Model

There is a need to evaluate the response of the global energy system to policies addressing climate change and the technology strategies associated to such a response. For this purpose, it is necessary to consider relevant climate variables within the energy-system modeling framework. A difficulty that arises when doing so is the fact that atmospheric interactions are complex and non-linear and uncertainty about them increases as one moves along the causal chain from emissions of greenhouse gases (GHG) towards atmospheric concentrations, radiative forcing and temperature change.

Here, following the work of Manne *et al.* (1995) and Manne and Richels (2004) for the integrated assessment MERGE model, we have implemented a linear representation of the atmospheric concentration of three main greenhouse gases, namely CO_2 , CH_4 and N_2O, in the energy-system Global Multi-regional MARKAL (GMM) model (Barreto, 2001; Barreto and Kypreos, 2004a,b; Rafaj *et al.*, 2005). This procedure allows imposing constraints on these variables in order to compute scenarios where stabilisation of GHG concentrations is to be achieved. The appendix A2 describes the GMM implementation in detail.

7.1. CO_2 concentration

The procedure to represent the atmospheric concentration of CO_2 relies on a simplified model for CO_2 concentration based on the idea that the impulse response function of an instantaneous injection of CO_2 to the atmosphere is linear and can be represented by the weighted summation of exponential functions (for a discussion see Joos and Bruno, 1996; Joos *et al.*, 1996).[4]

$$G(t) = \sum_{i=1}^{5} a_i * e^{-t/\tau_i} \quad (21)$$

Where: $\sum_{i=1}^{5} a_i = 1$ (22)

Each of these exponential functions represents the decay over time of a given fraction (a_i) of the injected CO_2, which has a given atmospheric lifetime, represented by the coefficient τ_i (in years). Each of these exponential functions is typically referred to as a "box". For this implementation we use five of these functions, or boxes, with the corresponding parameters taken from the MERGE model (Manne *et al.*, 1995; Manne and Richels, 2004) as summarized in Table 7.

[4] This, on its turn, uses the fact that the response of a linear system can be characterized by its impulse response function.

Table 7: Summary of the parameters of the exponential representation of the atmospheric response to CO_2

	1	2	3	4	5
fraction (a_i)	0.142	0.24	0.323	0.206	0.088
atmospheric lifetime τ_i (years)	inf	313.8	79.8	18.8	1.7

The caveat must be stated that this linear function is only valid for a CO_2 concentration that does not deviate substantially from the equilibrium concentration, which is assumed to be the pre-industrial level.

The total stock of CO_2 is computed as the summation of CO_2 stocks across all the boxes and the fraction of pre-industrial CO_2 emissions that are assumed to never decay.

$$Stock_{CO2,tp} = NCO2 + \sum_{box} CO2B_{box,tp} \quad (23)$$

NCO2: Pre-industrial level of CO_2 assumed never to decay (in Gt C).
$CO2B_{box,tp}$: CO2 stock per box and time period tp

For the base year (2000), this translates into the initial condition:

$$Bco2stock = NCO2 + \sum_{box} CO2base_{box} \quad (24)$$

Where:

NCO2: Pre-industrial level of CO_2 assumed never to decay (in Gt C). Here, this value is assumed to be 594 Gt C.
$CO2base_{box}$: Amount of CO_2 in each box in the starting year (2000) in Gt C.

In its turn, the stock of CO_2 in a given box and time period ($CO2B_{box,tp}$) depends on the previously available stock and the incoming emissions. The first term represents the decay of the CO_2 existing in the box in the previous period. The second term computes the decay of the emissions that enter a given box in every intervening year between time periods. For instance, when computing the CO_2 stock in a given box in the year 2010, these are the emissions entering the box in 2000, 2001….2009, and decaying afterwards.

$$CO2B_{box,tp+1} = CO2B_{box,tp} * \left(decay_{box}\right)^{\Delta t} + decay2_{box,tp} * frac_{box} * \sum_{reg} EM_{tp,reg,CO2} \quad (25)$$

Where:

$$decay_{box} = 1 - e^{\frac{-1}{\tau_i}} \quad (26)$$

$$decay2_{box,tp} = \sum_{nyr} \left(nyrtp_{nyr,tp} * decay_{box}\right)^{ord(nyr)-1} \quad (27)$$

The CO_2 concentration is computed as the ratio between the total stock in a given time period and the total stock in the base year multiplied by the concentration in the base year (2000).

$$CO2CON_{tp} = \frac{Stock_{CO2,tp}}{Bco2stock} * CO2CONM_{2000} \quad (28)$$

Notice that with this formulation, the CO_2 concentration depends linearly on the stock and one single variable could be used. However, we have chosen to specify variables for both concentration and stock.

The upper constraint on CO_2 concentration is defined as:

$$CO2CON_{tp} \leq CONM_{co2,tp} \quad (29)$$

Alternatively, an upper bound on the concentration variable can be specified, without defining an additional constraint for this purpose.

7.2. Concentration of CH_4 and N_2O

The calculation of atmospheric concentration for CH_4 and N_2O is based on a simple one box decay model proposed by Houghton *et al.* (1997). In this model the change of CH_4 concentration over time is expressed as follows:

$$\frac{dC}{dt} = \beta * E - C\left(\frac{1}{\tau_{atm}} + \frac{1}{\tau_{soil}}\right) \quad (30)$$

Where:

C: Atmospheric concentration
E: Mass emission rate per year
β: Conversion factor from mass to concentration
τ_{atm}: Mean lifetime of a CH_4 molecule in the atmosphere when accounting for chemical removal
τ_{soil}: Mean lifetime of a CH_4 molecule if absorption by soils were the only removal process.

In the MERGE model the above expression is simplified and a single mean lifetime of 12 years is used based on estimates of IPCC (2001).

As for N_2O, the expression for the change of concentration over time is given as:

$$\frac{dC}{dt} = \beta * E - C\left(\frac{1}{\tau_{atm}}\right) \quad (31)$$

Here, we use a mean lifetime (τ_{atm}) of 114 years according to estimates of IPCC (2001).

Following Manne and Richels (2004), in the formulation implemented in GMM the decay function is applied to the stock of the GHG above the natural equilibrium level.

$$addstock_{oghg,tp} = stock_{oghg,tp} - eqstock_{oghg} \quad (32)$$

Where:

addstock$_{oghg,tp}$: additional stock of the GHG above the equilibrium level
stock$_{oghg,tp}$: Total stock of the GHG
eqstock$_{oghg}$: Equilibrium GHG stock (pre-industrial level)

For the starting year (2000), this results in the following initial conditions:

$$addstock_{oghg,2000} = basestock_{oghg} - eqstock_{oghg} \quad (33)$$

With:

$$stock_{oghg,2000} = basestock_{oghg} \quad (34)$$

IPCC (2001) reports a global atmospheric burden of 4,850 Tg of CH_4 for the year 1998, corresponding to a concentration of 1745 ppb and a globally averaged surface abundance of 314 ppb for N_2O in 1998, corresponding to a global burden of 1510 Tg N. These values are used to define the stocks of CH_4 and N_2O in the base year in the MERGE model, the parameters are defined as follows:

basestock(CH4)=4.85 Gt CH_4, basestock(N_2O)=1.510 Gt N_2O

The equilibrium stock (eqstock$_{oghg}$) is assumed to be the pre-industrial level and in the model it is specified as a given fraction of the total stock of the gas in the base year (2000).

$$eqstock_{oghg} = \left(1 - pi_{oghg}\right) * basestock_{oghg} \quad (35)$$

In the MERGE model, pi(CH_4)=0.6 and pi(N_2O)=0.12. These values are used in the GMM model as well.

The decay of the additional stock follows a similar pattern as the one specified for CO_2. That is, the change of additional stock over time depends on the previously available stock and the incoming emissions. The first term represents the decay of the additional stock in the previous period. The second term computes the decay of the emissions taking place in every intervening year between time periods.

$$addstock_{oghg,tp+1} = addstock_{oghg,tp} * \left(odecay_{oghg}\right)^{\Delta t} + odecay2_{oghg,tp} * \sum_{reg} EM_{tp,reg,oghg} \quad (36)$$

Where:

$$odecay_{oghg} = 1 - e^{\frac{-1}{\tau_{oghg}}} \quad (37)$$

with τ_{CH4} =12 years, τ_{N2O} =114 years.

And:

$$odecay2_{oghg,tp} = \sum_{nyr} \left(nyrtp_{nyr,tp} * odecay_{oghg}\right)^{prd(nyr)-1} \quad (38)$$

The concentration of CH_4 and N_2O is specified as the ratio between the total stock in the time period tp and the stock in the base year multiplied by the concentration of the GHG in the base year:

$$OCON_{oghg,tp} = \frac{Stock_{oghg,tp}}{Basestock_{oghg}} * CONM_{oghg,2000} \quad (39)$$

The upper bound on CH_4, N_2O concentrations is defined as:

$$OCON_{oghg,tp} \leq CONM_{oghg,tp} \quad (40)$$

As an alternative, the GMM model can be been linked to the stylized climate model MAGICC version 4.1 (Wigley and Raper, 1997; Hulme *et al.*, 2000; Wigley, 2003). In this case, the GMM model provides energy-related CO_2 emissions, and total emissions of CH_4 and N_2O. Other emissions are exogenously specified following estimates from the IPCC/SRES B2 scenario (SRES, 2000). The link between the energy-system GMM model and climate MAGICC model allows estimating the following global climate indicators: atmospheric concentrations of CO_2, CH_4 and N_2O, annual-average global temperature change and annual-average global sea-level rise, the latter two relative to the year 1990.

8. Final Remarks

This report has presented the extensions to the “bottom-up” energy-systems GMM model undertaken at the Energy Economics Group (EEG) of the Paul Scherrer Institute (PSI) undertaken in the context of the EC-sponsored SAPIENTIA project and the Swiss National Centre for Competence in Research on Climate (NCCR-Climate). The changes allow improvements in the representation of the mechanisms of technological change in the global energy system in the GMM model and in the examination of the role of the energy system in the context of GHG mitigation strategies. In addition, the extensions presented here enhance the capabilities of the GMM modeling framework for the assessment of the impact of policy instruments on energy and climate-related indicators of sustainable development, which is an important element of the decision-support and policy-making processes of the European Commission (EC, 2002).

In order to adequately quantify the impact of energy-related R&D and D&D programs on sustainability indicators of interest in the areas of climate change, security of energy supply and transportation, among others, several features have been added to the GMM model. A clusters approach to the representation of technology learning, which allows different technologies to share a common “key learning component”, has been implemented. Also, the representation of the passenger transportation sector has been disaggregated and improved. Moreover, marginal abatement curves for two non-CO_2 greenhouse gases (CH_4 and N_2O) have been added. Also, a linear representation of the atmospheric concentration of CO_2, CH_4 and N_2O has been included. Other changes are related to the inclusion of additional technologies for production of synthetic fuels (hydrogen and Fischer-Tropsch liquids) and CO_2 capture in fossil-based and biomass-based electricity generation and hydrogen production technologies.

References

Barreto, L., 2001: *Technological Learning in Energy Optimisation Models and the Deployment of Emerging Technologies*. Ph.D. Thesis No 14151. Swiss Federal Institute of Technology Zurich (ETHZ). Zurich, Switzerland.

Barreto, L., Kypreos, S., 2004a: Emissions Trading and Technology Deployment in an Energy-Systems "Bottom-Up" Model with Technology Learning. *European Journal of Operational Research* **158**, 243-261.

Barreto, L., Kypreos, S., 2004b: Endogenizing R&D and Market Experience in the "Bottom-Up" Energy-Systems ERIS Model. *Technovation* **24**(8), 615-629.

Ciferno, J.P., Marano, J., 2002: *Benchmarking Biomass Gasification Technologies for Fuels, Chemicals and Hydrogen Production*. National Energy Technology Laboratory. US Department of Energy, Pittsburg, PA, USA.

David, J., Herzog, H., 2001: The Cost of Carbon Capture, *Proceedings of the 5th International Conference on Greenhouse Gas Control Technologies*, Williams, D., Durie, B., McMullan, P., Paulson, C. and Smith, A. (eds). CSIRO, pp. 985-990.

Delhotal, C., De la Chesnaye, F., Gallaher, M., Ross, M., 2003: *Technical Change in Energy-Related Methane Abatement*. Working Paper, U.S. Environmental Protection Agency. Washington D.C, USA.

Delhotal, C., Delaquil, P., Goldstein, G., 2004: *Modeling Methane and Deriving Mitigation Cost Curves in US-EPA MARKAL*. Paper presented to the International Energy Workshop, June 22-24, 2004, Paris, France.

De la Chesnaye, F., Harvey, R., Kruger, D., Laitner, J.A., 2001: Cost-effective Reductions of non-CO_2 Greenhouse Gases, *Energy Policy* **29**, 1325-1331.

EC (European Commission), 2001: *A Sustainable Europe for a Better World: A European Union Strategy for Sustainable Development*. Communication from the Commission COM(2001) 264 Final. European Commission. Brussels, Belgium.

EC (European Commission), 2002: *Communication from the Commission on Impact Assessment*. Document COM(2002) 276 Final. European Commission. Brussels, Belgium.

Fishbone, L.G., Abilock, H., 1981: MARKAL, a Linear-Programming Model for Energy Systems Analysis: Technical Description of the BNL Version, *International Journal of Energy Research* **5**, 353-375.

Fuglestvedt, J.S, Berntsen, T.K., Godal, O., Sausen, R., Shine, K.P., Skodvin, T., 2003: Metrics of Climate Change: Assessing Radiative Forcing and Emission Indices. *Climatic Change* **58**, 267-331.

GAMS., 1998: *GAMS: A user's guide*. GAMS Development Corporation. Washington D.C, USA.

Gritsevskyi, A., Nakićenović, N., 2000: Modeling Uncertainty of Induced Technological Change. *Energy Policy* **28**, 907-921.

Houghton, J.T., Gylvan Mira Filho, J., Griggs, D.J., Maskell, K., 1997: *An introduction to simple climate models used in the IPCC second assessment report*. Intergovernmental Panel on Climate Change. Geneva, Switzerland. February, 1997. http://www.ipcc.ch/pub/IPCCTP.II(E).pdf

Hulme, M., Wigley, T.M.L., Barrow, E.M., Raper, S.C.B., Centella, A., Smith, S.J. and Chipanshi, A.C., 2000: *Using a Climate Scenario Generator for*

Vulnerability and Adaptation Assessments: MAGICC and SCENGEN Version 2.4 Workbook, Climatic Research Unit, Norwich, UK, 52pp.

IPCC (Intergovernmental Panel on Climate Change), 2001: Summary for Policymakers (SPM). In: J. T. Houghton, Y. Ding, D.J. Griggs, M. Noguer, P. J. van der Linden and D. Xiaosu (eds.), *Climate Change 2001: The Scientific Basis*, Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), Cambridge University Press, UK. pp 944.

Kemp, R., 1997: *Environmental Policy and Technical Change. A Comparison of the Technological Impact of Policy Instrument*s. Edward Elgar, Cheltenham, UK.

Kouvaritakis, N., Soria, A., Isoard, S., 2000: Modeling Energy Technology Dynamics: Methodology for Adaptive Expectations Models with Learning by Doing and Learning by Searching. *Int. J. of Global Energy Issues* **14** (1/2/3/4), 104-115.

Joos, F., Bruno, M., 1996: Pulse response functions are cost-efficient tools to model the link between carbon emissions, atmospheric CO_2 and global warming. *Physics and Chemistry of the Earth* **21**, 471-476.

Joos, F., Bruno, M., Fink, R., Siegenthaler, U., Stocker, T., Le Quere, C., Sarmiento, J., 1996: An efficient and accurate representation of complex oceanic and biospheric models of anthropogenic carbon uptake. *Tellus* 48B, 397-417.

Krzyzanowski, D., 2006: *Conditions for the Market Penetration of Hydrogen Fuel Cell Cars in the Transportation Sector*. Ph.D. Thesis, Nr. 16692. ETH Zurich. Zurich, Switzerland.

Krzyzanowski, D.A., Kypreos, S., Barreto, L., 2006: Supporting Hydrogen Transportation: Case Studies of Governmental Policy Measures. Paper submitted to the *Journal of Computational Management Science* (Special Issue on Managing Energy and the Environment).

Loulou, R., Goldstein, G., Noble, K., 2004: *Documentation for the MARKAL Family of Models*. Energy Systems Technology Analysis Programme (ETSAP). International Energy Agency (IEA). http://www.etsap.org/MrklDoc-I_StdMARKAL.pdf

Manne, A., Mendelsohn, R., Richels, R., 1995: MERGE: A model for evaluating regional and global effects of GHG reduction policies. *Energy Policy* **23** (1), 17-34.

Manne, A., Richels, R., 2000: *A Multi-gas Approach to Climate Policy: with and without GWPs*. Working Paper. Stanford University, Stanford, USA.

Manne, A., Richels, R., 2004: *MERGE: An integrated assessment model for global climate change*. Working paper. Stanford University.
http://www.stanford.edu/group/MERGE/GERAD1.pdf

Manne, A., Richels, R., 2004: *The Role of Non-CO_2 Greenhouse gases and Carbon Sinks in meeting Climate Objectives*. Draft contribution to the EMF21. Stanford University. Stanford, CA, USA http://www.stanford.edu/group/MERGE/biblio.htm

Manne, A., Barreto, L., 2004: Learn-by-doing and Carbon Dioxide Abatement. *Energy Economics* **26** (4), 621-633

Messner, S., 1997: Endogenised Technological Learning in an Energy Systems Model. *Journal of Evolutionary Economics* **7**, 291-313.

Messner, S., Strubegger, M., 1995: *User's Manual of MESSAGE III*, WP-95-69, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria.

Nakićenović, N., 1997: *Technological Change as a Learning Process*. Paper presented to the IIASA Induced Technology Workshop, International Institute for Applied Systems Analysis, Laxenburg, Austria.

Olivier, J.G.J. and Berdowski, J.J.M., 2001: Global Emissions Sources and Sinks. In Berdowski, J., Guicherit, R. and B.J. Heij (eds.), *The Climate System*, pp. 33-78, A.A. Balkema Publishers/Swets & Zeitlinger Publishers, Lisse, The Netherlands, ISBN 90 5809 255 0.

Ogden, J.M., Williams, R.H., Larson, E.D., 2004: Societal Lifecycle Costs of Cars with Alternative Fuels/Engines, *Energy Policy* **32**, 7-27.

O'Neill, B.C., 2000: The Jury is still out on Global Warming Potentials. *Climatic Change* **44**, 427-443.

Parsons, E., Shelton, W., Lyons, J., 2002: *Advanced Fossil Power Systems Comparison Study*, prepared for the National Energy Technology Laboratory (USA), December, 2002.

Rafaj P., 2005: *Analysis of Policies Contributing to Sustainability of the Global Energy System Usi§ng the Global Multi-regional MARKAL Model (GMM)*, Ph.D. Thesis, Nr. 16122, ETH Zürich 2005. Zurich, Switzerland.

Rafaj, P., Kypreos, S., Barreto, L., 2005. Flexible Carbon Mitigation Policies: Analysis with a Global Multi-regional MARKAL Model. In Haurie, A., Viguier, L., (Editors) *Coupling Climate and Economic Dynamics* Kluwer Academic Publishers. Dordrecht, The Netherlands. ISBN 1-4020-3424-5.

Rafaj, P., Kypreos, S., Barreto, L., 2006: Combining Policy Instruments for Sustainable Energy Systems: An Analysis with the GMM Model. *Environmental Modelling and Assessment* (in press).

Rafaj, P., Kypreos, S., 2006: Internalization of External Cost in the Power Generation Sector: Analysis with Global Multi-regional MARKAL Model. *Energy Policy* (in press).

Rao, S., Riahi, K., 2004: The Role of non-CO_2 Greenhouse Gases in Climate Change Mitigation: Long-term Scenarios for the 21st Century. *Energy Economics* (forthcoming).

Reilly, J., Prinn, R., Harnisch, J., Fitzmaurice, J., Jacoby, H., Kicklighter, D., Melillo, J., Stone, P., Sokolov, A., Wang, C., 1999: Multi-gas Assessment of the Kyoto Protocol *Nature* **401**, 549-555.

Reilly, J., Jacoby, H., Prinn, R., 2003: *Multi-gas Contributors to Global Climate Change: Climate Impacts and Mitigation Costs of non-CO_2 Gases*. Pew Center on Global Climate Change. Washington, US.

Riahi, K., Roehrl, R.A., 2000: Greenhouse Gas Emissions in a Dynamics-as-Usual Scenario of Economic and Energy Development. *Technological Forecasting and Social Change* **63**,175-20

Sahal, D., 1980: Technological Progress and Policy. In Sahal, D. (Editor). *Research, Development, and Technological Innovation. Recent Perspectives in Management*. Lexington Books. Lexington, Massachusetts.

Schafer, A., 1995: *Trends in Global Motorized Mobility; The Past 30 Years and Implications for the Next Century*. WP-95-49, International Institute of Applied Systems Analysis, Laxenburg, Austria.

Schafer, A., 1998: The Global Demand for Motorized Mobility, *Transportation*

Research Part A **32**(6), 455-477
Seebregts, A., Bos S., Kram T., Schaeffer G., 2000: Endogenous Learning and Technology Clustering: Analysis with MARKAL Model of the Western European Energy System, *Int. J of Global Energy Issues* **14**(1/2/3/4), 289-319.
Silverberg, G., 1991: Adoption ad Diffusion of Technology as a Collective Evolutionary Process. *Technological Forecasting and Social Change* **39**, 67-80.
Simbeck, D.R., Chang, E., 2002: *Hydrogen Supply: Cost Estimate for Hydrogen Pathways – Scoping Analysis,* SFA Pacific, Inc., Mountain View, California
Turton, H., Barreto, L., 2004: *The Extended Energy-Systems ERIS Model: An Overview*. Interim Report IR-04-010. International Institute for Applied Systems Analysis. Laxenburg, Austria. February, 2004. <http://www.iiasa.ac.at/Publications/Documents/IR-04-010.pdf>
Turton, H., Barreto, L., 2006: Cars, Hydrogen and Climate Change: A Long-term Analysis with the ERIS Model. *International Journal of Energy Technology and Policy* (in press).
<http://www.iiasa.ac.at/Research/ECS/docs/Barreto_saee_2004.pdf>
Watanabe, C., 1999: *Industrial Dynamism and the Creation of a "Virtuous Cycle" between R&D, Market Growth and Price Reduction. The Case of Photovoltaic Power Generation (PV) Development in Japan*. Paper presented to the IEA International Workshop on Experience Curves for Policy Making - The Case of Energy Technologies. Stuttgart, Germany. 10-11 May, 1999.
WBCSD (World Business Council for Sustainable Development), 2001: *Mobility 2001: World Mobility at the End of the 20th Century and its Sustainability*. World Business Council for Sustainable Development. Geneva, Switzerland.
WBCSD (World Business Council for Sustainable Development), 2004: *Mobility 2030: Meeting the Challenges to Sustainability*. World Business Council for Sustainable Development. Geneva, Switzerland.
Weiss, M., Heywood, J., Drake, E., Schafer, A., Auyeung, F., 2000: *On the Road in 2020: A Life-cycle Analysis of new Automobile Technologies*. Energy Laboratory Report # MIT EL-00-003. Massachusetts Institute of Technology. Cambridge, Massachusetts, USA.
Weiss, M.A., Heywood, J.B., Schafer, A., Natarajan, V.K., 2003: *Comparative Assessment of Fuel Cell Cars*, MIT LFEE 2003-001 RP. Massachusetts Institute of Technology. Cambridge, MA, USA.
Wigley, T.M.L., Raper, S.C.B., 1997: *Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC Version 2.3.)*, The Climate Research Unit, University of East Anglia, UK.
Wigley, T.M.L., 2003: *MAGICC/SCENGEN 4.1: Technical Manual*. University Corporation of Atmospheric Research. Boulder, CO, USA.
Yamashita, K., Barreto, L., 2004: *Biomass Gasification for the Co-production of Fischer-Tropsch Liquids and Electricity*. Interim Report IR-04-047. International Institute for Applied Systems Analysis. Laxenburg, Austria. October, 2004. < http://www.iiasa.ac.at/Publications/Documents/IR-04-047.pdf>
Yamashita, K., Barreto, L., 2005: Integrated Energy Systems for the 21st Century: Coal Gasification for Co-producing Hydrogen, Electricity and Fuels. *Energy* 30, 2453-2473.

Appendix A1. Implementation of Marginal abatement curves in the GMM model

In this section the implementation of the marginal abatement curves in the GMM model are presented and the changes to the RMARKAL code necessary for the implementation of the MACs are listed. Files where changes were made are renamed and called separately to run the model.

Sets

1. Set defining steps for the marginal abatement curves

SET MSTEP

/ 1*11 /

2. Set defining the non-CO_2 GHGs to be considered

SET GHG

/CH4COA, CH4GAS, CH4OIL, CH4SWM, CH4MAN, N2ONI, N2OADI/

Where:

CH4COA: CH4 from coal production
CH4GAS: CH4 from gas production
CH4OIL: CH4 from oil production
CH4SWM: CH4 from solid waste management
CH4MAN: CH4 from manure management
N2ONI: N2O from nitric acid production
N2OADI: N2O from adipic acid production

These are the categories for which the US EPA (2003) provides MACs

3. Set defining the energy-related GHGs, namely CH_4 from coal, oil and gas production. These GHGs have endogenous baseline emissions.

SET ERGHG(GHG)

/ CH4COA, CH4GAS, CH4OIL /

4. Set defining the non-energy-related GHGs (i.e. CH_4 from solid waste management and manure management and N_2O from adipic and nitric acid production). For these sources an exogenous baseline is considered in this approach

SET NERGHG(GHG)

/ CH4SWM, CH4MAN, N2ONI, N2OADI/

5. Set defining other sources of non-abateable GHGs (i.e. for which MACs are not specified)

SET GHGOS

/ CH4OS, N2OOS/

Where

CH4OS CH_4 emissions from enteric fermentation and rice paddies
N2OOS N_2O emissions from soils

6. Set defining total C-eq emissions (i.e. CO_2+CH_4+N_2O)

SET CEQ / CEQ /

7. Set mapping the GHG categories to C-eq emissions

SET GHGTOCEQ(GHG,CEQ)

/ CH4COA.CEQ, CH4GAS.CEQ, CH4OIL.CEQ, CH4SWM.CEQ, CH4MAN.CEQ, N2ONI.CEQ, N2OADI.CEQ /

In principle, more than one element could be declared in SET CEQ. If so, the GHGs categories could be associated to different C-eq subgroups.

8. Other sets

SET REG Regions

SET TP Time period

SET SEP(SRC,ENT,P) Supply Steps

SET ENV 'Environmental Indicators'

Three additional regional environmental indicators have been added to account for CH_4 emissions from oil, coal and gas production.

```
C4O    'CH4 from oil               '
C4C    'CH4 from coal              '
C4G    'CH4 from gas               '
```

Set defining the sub-set of environmental indicators related to CH_4 emissions

SET ENV1(ENV) 'Environmental Indicators'

```
/
   C4O    'CH4 from oil               '
   C4C    'CH4 from coal              '
   C4G    'CH4 from gas               '
   /
```

The pollutants C4O, C4C and C4G should be added to the set ENV in the *.dd file for the computation of energy-related CH_4 emissions (from oil, coal and gas production respectively). C4C should be defined both for lignite and coal resources.

SET G_TRADE(*)

The C-eq emissions (CEQ) should be added to the set of commodities being traded

These are standard sets in MARKAL

9. Set mapping the regional environmental indicators (ENV) associated to regional energy-related CH4 emissions to the ERGHG set

SET ETOERGHG(ENV1,REG,ERGHG)

/
C4C.ASIA.CH4COA
C4G.ASIA.CH4GAS
C4O.ASIA.CH4OIL
C4C.EEFSU.CH4COA
C4G.EEFSU.CH4GAS
C4O.EEFSU.CH4OIL
C4C.LAFM.CH4COA
C4G.LAFM.CH4GAS
C4O.LAFM.CH4OIL
C4C.OOECD.CH4COA
C4G.OOECD.CH4GAS
C4O.OOECD.CH4OIL
C4C.NAM.CH4COA
C4G.NAM.CH4GAS
C4O.NAM.CH4OIL
/

Parameters

1. Reference abatement potentials

The abatement potentials of both energy-related (ER) and non-energy-related (NER) non-CO_2 GHG emissions must be specified.

Table ABTPREF_R(GHG,MSTEP,REG)

Abatement potential per price step, region, and GHG (defined in relative terms to the baseline) for a reference time period (i.e. 2010). An example is given below.

These potentials could also be specified as a function of time but that would require a number of additional tables. The assumption here is that they are specified for 2010 and potentials for other periods would be computed by the model using the technical-progress multipliers below.

	NAM	OOECD	EEFSU	ASIA	LAFM
CH4COA.1	0.665	0.602	0.790	0.842	0.680
CH4COA.2	0.860	0.618	0.790	0.842	0.855
CH4COA.3	0.860	0.618	0.790	0.842	0.855
CH4COA.4	0.860	0.618	0.790	0.842	0.855
CH4COA.5	0.860	0.618	0.790	0.842	0.855
CH4COA.6	0.860	0.618	0.790	0.842	0.855
CH4COA.7	0.860	0.618	0.790	0.842	0.855
CH4COA.8	0.860	0.618	0.790	0.842	0.855
CH4COA.9	0.860	0.618	0.790	0.842	0.855
CH4COA.10	0.860	0.618	0.790	0.842	0.855
CH4COA.11	0.860	0.618	0.790	0.842	0.855

2. Technical-progress multipliers

Table ABTM_R(GHG,REG,YEAR) Technical progress multipliers for abatement curves per GHG, region and time period.

3. Total abatement potentials per time period

The total abatement potentials per time period, region and GHG are defined as (given in relative terms, i.e. percentage or fraction):

ABATEPOT_R(GHG,MSTEP,REG,TP)=ABTM_R(GHG,
REG,TP)*(ABTPREF_R(GHG,MSTEP,REG)-ABTPREF_R(GHG,MSTEP-1,REG));

This formulation implies that the reference abatement potentials ABTPREF_R (GHG, MSTEP, REG) are given by the user in a cumulative way. That is, if for the first segment a potential of 30% that can be abated at 10$/ton C-eq is given and for the second segment a potential of 50% is specified, which can be abated at 20 $/ton C-eq, this means that 20% (i.e. 50%-30%) of emissions can be abated at 20 $/ton C-eq.

To avoid abatement of emissions beyond the baseline emissions the following expression is necessary

ABATEPOT_R(GHG,MSTEP,REG,TP) =
min(ABATEPOT_R(GHG,MSTEP,REG,TP), 1);

Use 1 if the coefficient ABATEPOT_R is defined as fraction. If it is defined as a percentage, then the 1 above should be changed to 100.

4. Abatement cost steps

Table ABATCOST_R(MSTEP,GHG) "abatement costs in US$/ton C eq"

The abatement costs for each MAC step, i.e. the carbon-equivalent prices being used in the curve definition. The table below is an example given in US$/ton C-eq using the steps provided by the US EPA (2003) study.

Table ABATCOST_R(MSTEP, GHG) "abatement costs in US$/ton C-eq"

	CH4COA	CH4GAS	CH4OIL	CH4SWM	CH4MAN	N2ONI	N2OADI
1	10	10	10	10	10	10	10
2	20	20	20	20	20	20	20
3	30	30	30	30	30	30	30
4	40	40	40	40	40	40	40
5	50	50	50	50	50	50	50
6	75	75	75	75	75	75	75
7	100	100	100	100	100	100	100
8	125	125	125	125	125	125	125
9	150	150	150	150	150	150	150
10	175	175	175	175	175	175	175
11	200	200	200	200	200	200	200

;

5. Exogenous baseline for non-energy-related GHG with MACs

For the sources of non-CO_2, non-energy-related GHG for which a MAC is defined (i.e. those belonging to the NERGHG set).

BLINE_R(NERGHG,REG,YEAR) baseline emissions (C-eq) per GHG, region, time period

Since our approach assumes that the emissions are given in terms of C-eq, in case they are defined originally in tons of CH_4 or N_2O, global warming potentials (GWP) should be used to convert them.

The US EPA study provides baselines only up to the year 2020. Therefore, they must be extrapolated to other periods assuming a given growth rate.

	1990	2000	2010	2020	2030	2040	2050
CH4SWM.NAM	69.28	67.31	67.17	59.61	58.56	55.64	52.73
CH4SWM.OOECD	50.53	44.76	43.43	45.98	42.44	40.94	39.44
CH4SWM.EEFSU	35.98	31.15	29.25	30.76	27.40	25.64	23.89
CH4SWM.ASIA	27.16	41.80	59.58	84.02	100.23	119.07	137.90

CH4SWM.LAFM 41.12 49.96 62.35 78.50 89.12 101.57 114.02

6. Exogenous baseline emissions for non-energy-related, non-abateable GHGs (without MACs)

Non-CO_2 GHG emissions from other sources for which a MAC is not specified are by definition non-abatable. However, they are necessary for comprehensiveness in reporting total C-eq emissions. Therefore, baseline emissions should also be defined for these sources as well.

BLINEOS_R(GHGOS, REG, YEAR) baseline emissions (C-eq), GHGOS, region, time period

7. Coefficients for CH_4 emissions from oil, gas and coal production

These coefficients can be included in the following table in the *.dd file, where the coefficients for other pollutants such as CO_2 are computed.

TABLE ENV_TACT(ENV,TCH,YEAR)

The CH_4 specific emissions (in ton C-eq/GJ or a similar unit) are defined separately for oil, gas and coal production to facilitate the computation of the corresponding energy-related baseline emissions below.

Variables

POSITIVE VARIABLES

R_ABATE(GHG,MSTEP,REG,TP) abatement per GHG, price step, region and time period.

R_EREM(GHG,REG,TP) Energy-related baseline GHG emissions, region, time period

R_EMGHG(GHG,REG,TP) Energy-related GHG emissions per region and time period (i.e. baseline minus abatement)

R_CEQEM(REG,TP) Regional C-eq emissions (CO2+CH4+N2O)

R_CEQGLOEM(TP) Global C-eq emissions (CO2+CH4+N2O)

Equations

MR_EMGHG1(ERGHG,REG,TP) annual energy-related ghg emissions
MR_EMGHG2(NERGHG,REG,TP) annual non-energy-related ghg emissions
MR_EREMGHG(ERGHG,REG,TP) annual energy-related baseline ghg emissions
MR_CEQEM (REG,TP) annual carbon eq. emissions (CO2+CH4+N2O) per region
MR_CEQGLOEM(TP) annual global carbon eq. emissions (CO2+CH4+N2O)
MR_ABPOT1(ERGHG,MSTEP,REG,TP) abatement for energy-related GHGs
MR_ABPOT2(NERGHG,MSTEP,REG,TP) abatement - non-energy related GHGs
MR_GTRDCEQ(TP,CEQ) Global trade of C-eq emissions
MR_PGTRDCEQ(%3TP,CEQ) Global trade of C-eq emissions - positive exports

1. Abatement for energy-related (endogenous baseline) non-CO_2 GHGs

MR_ABPOT1(ERGHG,MSTEP,REG,TP)..R_ABATE(ERGHG,MSTEP,REG,TP) =L= ABATEPOT_R(ERGHG,MSTEP,REG,TP)*R_EREM(ERGHG,REG,TP);

2. Abatement for non-energy-related (exogenous baseline) non-CO_2 GHGs

MR_ABPOT2(NERGHG,MSTEP,REG,TP)..R_ABATE(NERGHG,MSTEP,REG,TP) =L= ABATEPOT_R(NERGHG,MSTEP,REG,TP)*BLINE_R(NERGHG,REG,TP);

3. Annual energy-related baseline non-CO_2 GHG emissions per region and fuel (oil, coal, gas)

```
MR_EREMGHG(ERGHG,REG,TP)..

R_EREM(ERGHG,REG,TP) =E=

SUM(ENV1$(ETOERGHG(ENV1,REG,ERGHG)), R_EM(REG,TP,ENV1));
```

4. Energy-related annual non-CO_2 GHG emissions per region, time period

```
MR_EMGHG1(ERGHG,REG,TP)..R_EMGHG(ERGHG,REG,TP)=E=

R_EREM(ERGHG,REG,TP)

        - SUM(MSTEP, R_ABATE(ERGHG,MSTEP,REG,TP));
```

5. Non-energy-related annual non-CO_2 GHG emissions per region and time period

```
MR_EMGHG2(NERGHG,REG,TP)..R_EMGHG(NERGHG,REG,TP) =E=

BLINE_R(NERGHG,REG,TP)

        - SUM(MSTEP, R_ABATE(NERGHG,MSTEP,REG,TP));
```

6. Annual C-eq emissions (CO_2+CH_4+N_2O) per region and time period

```
MR_CEQEM(REG,TP)..R_CEQEM(REG,TP)=G=          SUM(GHG,R_EMGHG(GHG,REG,TP))+
SUM(GHGOS, BLINEOS_R(GHGOS, REG,TP))

* plus CO2 emissions (check this)

+ %4EM(%5TP,%2"COX")

* plus trade of C-eq emissions

+ SUM(CEQ, R_NTXTRD(REG,TP,CEQ));
```

7. Global annual C-eq emissions (CO_2+CH_4+N_2O) per time period

```
MR_CEQGLOEM(TP)..R_CEQGLOEM(TP)=E=SUM(REG,R_CEQEM(REG,TP));
```

8. Global trade of C-eq emissions

```
MR_GTRDCEQ(TP,CEQ) ..
  SUM(REG,MMSCALE_R(REG) * R_NTXTRD(REG,TP,CEQ) * REG_XCVT(REG,CEQ) )
=E=
  0;

* Additional constraint for global trade of C-eq emissions

MR_PGTRDCEQ(REG,TP,CEQ)$TRD_COST(CEQ) ..
  R_NTXTRD(REG,TP,CEQ) =L= R_EXPTRD(REG,TP, CEQ)
 ;
```

9. Changes to the objective function

The objective function. i.e. total discounted system costs, is modified to reflect the costs of the non-CO_2 abatement. That is, a term of the following form is added (MMEQPRIC.INC):

```
+SUM(REG,SUM(TP,PRI_DF_R(REG,TP)*(SUM((MSTEP,GHG),
ABATCOST_R(MSTEP,GHG)*R_ABATE(GHG,MSTEP,REG,TP)))))
```

Where PRI_DF is the discount factor:

```
PRI_DF(TP) =
   SUM(ALLORD$(ORD(ALLORD) LE NYRSPER), (1 + DISCOUNT) ** (1 - ORD(ALLORD))) /
   ((1 + DISCOUNT) ** (- STARTYRS + NYRSPER * (ORD(TP) - 1)));
```

Appendix A2. Implementation of GHG concentrations in the GMM model

In what follows we describe the implementation of GHG concentrations in the GMM model using the standard GAMS notation (GAMS, 1998) and list the corresponding RMARKAL code

A2.1 CO_2 concentration

SETS

BOX Number of exponential functions for the decay of CO2 in the atmosphere

/BOX1, BOX2, BOX3, BOX4, BOX5/

NYR Number of years /1*NYRSPER/

GHGT Set of GHGs /C2T, CH4, N2O/;

C2T represents total CO_2. It is labelled C2T in order to avoid naming conflicts with the pollutant CO_2 declared in the GMM data files.

TP time periods /2000, 2010, 2020, 2030, 2040, 2050, 2060, 2070, 2080, 2090, 2100, 2110 /;

SCALARS

NCO2 Pre-industrial level of CO2 assumed never to decay /594/
NYRSPER Number of years per period /10/

Parameters

DECAY_R(BOX) yearly decay factor for each box
DECAY2_R(BOX,TP) period decay factor for each box
NYRTP_R(TP, NYR) Multiplier to compute the decay factor decay2
FRAC_R(BOX) Fraction of CO2 emissions decaying in a given box
BCO2STOCK_R Base-year stock of CO2
CO2BASE_R(BOX) Base level of CO2 emissions within a box
CONM_R(GHGT, TP) Maximum GHG concentration for a given time period

Variables

R_CO2B(BOX,TP) CO2 stock per box and time period
R_STOCK(GHGT, TP) GHG stock per time period
R_CO2CON(TP) CO2 concentration per time period
R_EM(REG,TP,ENV) Emissions of pollutant per region and time period

Equations

MR_CO2BOX (BOX, TP) Decay of CO2 stock in a given box
MR_CO2STOCK (TP) Total CO2 stock as a summation of CO2 stocks across boxes
MR_CO2CON(TP) CO2 concentration as a function of CO2 stock
MR_CO2CONM(TP) Upper bound on CO2 concentration

PARAMETER

BCO2STOCK_R=NCO2+SUM(BOX, CO2BASE_R(BOX));

DECAY2_R(BOX,TP)=SUM(NYR,(NYRTP_R(TP, NYR)*DECAY_R(BOX))**(ORD(NYR)-1)));

EQUATIONS

Equation (3)

MR_CO2STOCK(TP)..R_STOCK(GHGT,TP)$ORD(GHGT EQ 1)=E=SUM(BOX, R_CO2B(BOX,TP))+NCO2;

Equation (5)

MR_CO2BOX(BOX,TP+1)..R_CO2B(BOX,TP+1)=E=R_CO2B(BOX,TP)*DECAY_R(BOX)**NYR SPER+ DECAY2_R(BOX,TP)*FRAC_R(BOX)*SUM(REG, R_EM(REG,TP,"COX"));

Equation (8)

* CO2 concentration as a function of total CO2 stock

MR_CO2CON(TP)..R_CO2CON(TP)=E=(SUM(GHGT$(ORD(GHGT) EQ 1), CONM_R(GHGT,"2000"))/ BCO2STOCK_R)*(SUM(GHGT$(ORD(GHGT) EQ 1),R_STOCK(GHGT,TP)));

Equation (9)

* Upper bound for CO2 concentration
MR_CO2CONM(TP).. R_CO2CON(TP)=L=SUM(GHGT$(ORD(GHGT) EQ 1),CONM_R(GHGT,TP));

Bounds

* LB* Bounds on CO2 stock in each box

R_CO2B.FX(BOX,"2000")=CO2BASE_R(BOX);

* LB* Bounds on total CO2 stock over time

* R_STOCK.UP(GHGT,TP)$(ORD(GHGT) EQ 1)=BCO2STOCK_R*CO2CONM_R(TP)/CO2CONM_R("2000");

R_STOCK.UP(GHGT,TP)$(ORD(GHGT) EQ 1)=792.46*CONM_R(GHGT, TP)/CONM_R(GHGT,"2000");

SCALARS

NCO2 /594/;

LB parameters for GHG concentrations

PARAMETERS

DECAY_R(BOX)

/
BOX1 1.000000000
BOX2 0.996818329
BOX3 0.987546862

BOX4 0.948198425
BOX5 0.555306373
/

PARAMETERS

FRAC_R(BOX)

/
BOX1 0.142
BOX2 0.241
BOX3 0.323
BOX4 0.206
BOX5 0.088
/

PARAMETERS

CO2BASE_R(BOX)

/
BOX1 44.444
BOX2 66.461
BOX3 65.929
BOX4 20.310
BOX5 1.316
/

A2.2 CH_4 and N_2O concentration

SETS

GHGT Set of GHGs /CO2, CH4, N2O/;
OGHG(GHGT) Non-CO_2 GHGs /CH4, N2O/;
NYR Number of years /1*NYRSPER/

SET GHG Non-CO2 GHG
/ CH4COA, CH4GAS, CH4OIL, CH4SWM, CH4MAN, N2ONI, N2OADI/

SET GHGOS Other sources Non-CO2 GHG / CH4OS , N2OOS/

The following sets map the categories for which marginal abatement curves (MAC) are specified to the aggregate categories CH4 and N2O.

GHGTOG(GHG,OGHG) Mapping from GHG to OGHG
/ CH4COA.CH4, CH4GAS.CH4, CH4OIL.CH4, CH4SWM.CH4, CH4MAN.CH4, N2ONI. N2O, N2OADI.N2O /

GHGOSTOG(GHGOS,OGHG) Mapping from other sources of GHG to OGHG

/ CH4OS.CH4, N2OOS. N2O /

SCALARS

NYRSPER Number of years per period /10/

PARAMETERS

ODECAY_R(OGHG) yearly decay factor for each GHG

ODECAY2_R(OGHG,TP) period decay factor for each GHG
NYRTP_R(TP, NYR) Multiplier to compute the decay factor decay2
PI_R(OGHG) Pre-industrial fraction of GHG stock
EQSTOCK_R(OGHG) Equilibrium stock of a given non-CO_2 GHG (pre-industrial)
BASESTOCK_R(OGHG) Base year stock of a given non-CO_2 GHG (year-2000)
CONM_R(GHGT, TP) Maximum GHG concentration for a given time period

VARIABLES

R_STOCK(OGHG,TP) Stock of a given non-CO_2 GHG in period t
R_ADDSTOCK(OGHG,TP) Additional stock of a given Non-CO_2 GHG in period t
R_EMGHG(GHG,REG,TP) Emissions of each GHG category per region and time period t
R_EMOGHG(OGHG,TP) Global emissions of each GHG per time period t
R_OCON(OGHG,TP) Non-CO2 GHG concentrations

EQUATIONS

MR_EMOGHG(OGHG,TP) Global non-CO2 GHG emissions
MR_ADDSTOCK(OGHG,TP) Additional stock as a differential between stock and equilibrium stock
MR_ADDSTDECAY(OGHG,TP) Decay of additional stock of non-CO2 GHGs
MR_OCON(OGHG,TP) CH4,N2O concentration as a function of stock
MR_OCONM(OGHG,TP) Upper bound for CH4,N2O concentration

PARAMETERS

EQSTOCK_R(OGHG)=(1-PI_R(OGHG))* BASESTOCK_R(OGHG);

ODECAY2_R(OGHG,TP)=SUM(NYR,NYRTP_R(TP,NYR)*ODECAY_R(OGHG)**(ORD(NYR)-1));

EQUATIONS

* Total non-CO2 emissions (CH4,N2O) per time period

%1_EMOGHG(OGHG,TP)..
%4EMOGHG(OGHG,TP)=E=(44*0.001/(12*GWP%3(OGHG)))*SUM((%5GHG)$GHGTOG(GHG, OGHG), %4EMGHG(GHG,%5TP))+
(44*0.001/(12*GWP%3(OGHG)))*SUM((%5GHGOS)$(GHGOSTOG(GHGOS,OGHG)), BLINEOS%3(GHGOS, %5TP));

* Additional stock of CH4, N2O as the difference between stock and equilibrium stock

%1_ADDSTOCK(OGHG,TP)..%4ADDSTOCK(OGHG,TP)=E= %4STOCK(OGHG,TP)-EQSTOCK%3(OGHG);

* Decay of additional CH4, N2O stock over time

%1_ADDSTDECAY(OGHG,TP+1)..%4ADDSTOCK(OGHG,TP+1)=E=
%4ADDSTOCK(OGHG,TP)*ODECAY%3(OGHG)**NYRSPER+ODECAY2%3(OGHG,TP)*%4EMOGHG(OGHG,TP);

* CH4,N2O concentration as a function of total stock

%1_OCON(OGHG,TP)..%4OCON(OGHG,TP)=E=(CONM%3(OGHG,"2000")/BASESTOCK%3(OGHG))*%4STOCK(OGHG,TP);

```
* Upper bound for CH4,N2O concentration

%1_OCONM(OGHG,TP).. %4OCON(OGHG,TP)=L=CONM%3(OGHG,TP);

Bounds

R_STOCK.FX(OGHG,"2000")= BASESTOCK_R(OGHG);
```