Achieving CO_2 Emission Reductions Through Local-Scale Energy Systems Planning: Methods and Pathways for Switzerland

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Key messages

- An approach combining clustering techniques and cost optimization modeling is applied to assess local energy systems within Switzerland under a climate policy.
- Key local energy system archetypes are analyzed and demonstrate a significant collective decarbonization potential in the long-term.
- CO_2 taxes, building renovations, and decentralized generation technologies (e.g., solar photovoltaics) are instrumental in reducing local-scale carbon emissions.

1 Introduction

Today, urban areas accommodate the majority of the world's population and account for more than 70% of global energy-related CO_2 emissions (Edenhofer et al. 2015). As urban populations are expected to grow even larger in the long-term, local energy systems planning has the potential to play a key role in carbon mitigation efforts. That is, in order to achieve a mean global temperature increase of less than 2 °C by the turn of the century, carbon mitigation strategies should involve the active participation of policymakers not only on an international or national level, but also on a local scale.

Given the broad focus of climate and energy strategies, energy system models tend to focus on analysis at the national or international level. However, methods are needed to characterize and evaluate the range of local energy systems within a

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nation, enabling policymakers to define effective local climate policies within international climate agreements.

This study presents an approach which applies clustering techniques to identify characteristic urban, rural, and suburban energy systems in a case study for Switzerland. These characteristic communities (or archetypes) are then analyzed using a flexible, community cost optimization energy systems model built using the TIMES framework. The performance of each characteristic community is analyzed under climate-stringent national energy policy conditions, enabling policymakers to identify key community players in Switzerland's climate policy arena.

Switzerland ratified the Paris Agreement on Climate Change in 2017, committing itself to reducing national emissions by 50% in 2030 compared to 1990 levels (Swiss Federal Council 2017). Switzerland has further outlined intentions to reduce emissions by 70–85% by 2050. These reductions correspond to CO_2 emission rates of approximately 3 tonnes of CO_2 per capita in 2030, and 1–2 tonnes of CO_2 per capita in 2050 (Swiss Federal Council 2015). Although these targets do not aim for carbon neutrality by 2050, they reflect Switzerland's targets within the Paris Agreement and it is of interest to investigate the local-scale pathways by which these emission reductions can be achieved.

The New Energy Policy (NEP) outlined by the Swiss Federal Office of Energy in (Kirchner et al. 2012) follows the aforementioned reduction targets. The NEP strategy assumes strong efficiency improvements over time with respect to end-use technologies and building space heat demand via renovation measures. High CO_2 taxes are also assumed, reaching approximately 140 Swiss Francs (CHF) per tonne of CO_2 by 2050.

The energy system model in this study focuses on the heat and electricity demands of communities, across residential, commercial, industrial, and agriculture sectors. The cost optimal role of decentralized generation and storage technologies (DGSTs), and local energy resources are evaluated in the long-term (until 2050) in archetype communities under the NEP strategy.

Overall, the presented clustering and cost optimization community modeling approach can be utilized by policymakers to identify which types of communities have the most potential to contribute to national emission reductions, and what the pathways are to achieving these reductions cost optimally. Although demonstrated for Switzerland, the approach is general and can be adapted and applied to different scopes and scales.

2 Methodology

The approach consists of two main parts. Clustering techniques are first applied to municipal data sets in order to identify characteristic community energy systems (archetypes). Key archetypes are then modeled individually using a least-cost optimization, community energy systems model. This enables an evaluation of the cost optimal role of DGSTs and local energy resources in the long-term across key archetypes under NEP scenario conditions.

The clustering and modeling steps are described in the following sections. Further details on the approach and data inputs are provided in Yazdanie (2017).

2.1 Community Energy System Characterization Using Clustering

Clustering algorithms aim to separate data sets into unique groups of similar objects based on given criteria. A wide range of clustering algorithms and applications exist. With respect to the energy sector, clustering techniques are often applied to characterize building performance (Santamouris et al. 2007; Xiao et al. 2012; Nikolaou et al. 2012; Gao and Malkawi 2014). They have also been applied to characterize municipal heating systems in a small Swiss canton (Trutnevyte et al. 2012). However, clustering techniques have not been applied to characterize local energy systems on a national scale, with respect to the municipal characteristics considered in this study, to the best of the author's knowledge.

Swiss municipal energy systems are characterized with respect to three criteria: the developed environment classification (DEC) (urban, rural or suburban), local energy resource potentials (ERPs), and current energy usage shares (EUS). These criteria have been selected based on available data. Decentralized generation ERPs include rooftop solar irradiance, municipal waste, local wood production, small hydro, and manure. EUS refer to the contribution of six energy carriers (oil, natural gas, wood, district heating, other heating, and electricity) to the current total heat and electricity supply mix across the four evaluated sectors. Input data sets for Switzerland's approximately 2300 municipalities are determined using several sources (Hertach 2012; Swiss Federal Office of Energy 2013; Eymann et al. 2014; Buffat 2016; National Forest Inventory 2016; Panos and Ramachandran 2016; Swiss Federal Office of Statistics 2016a, b; Vögelin et al. 2016).

K-means clustering is applied to data sets using Lloyd's algorithm (Lloyd 1982). This algorithm partitions data sets into k unique clusters based on the Euclidean distance, minimizing the within-cluster sum of squared errors (WCSS):

$$\mathrm{WCSS} = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2,$$

where C_i is the ith of k clusters, x is the set of data points belonging to cluster C_i, and μ_i is the average (or centroid) of cluster C_i. Cluster centroids are first initialized; a range of methods can be applied for this purpose (e.g., cluster centroids may be randomly initialized). Data points are then assigned to the nearest cluster centroid. Cluster centroids are recalculated and data points are reassigned to the nearest cluster centroid. This process is repeated until convergence, whereby the final clusters and centroids are established.

In this study, each data point represents one municipality, which is defined by its characteristic data. The value for k is predetermined using the silhouette criterion (Rousseeuw 1987). K-means is repeated several times and cluster centroids are initialized using the heuristics-based k-means++ algorithm (Arthur and Vassilvitskii 2007). Averaged centroids over these repeated runs serve as initial centroids for a final run. Further details on the clustering approach are provided in (Yazdanie 2017).

The clustering approach yields several characteristic archetypes. Each archetype consists of several municipalities and is distinguished by a unique combination of DEC, ERP, and EUS cluster characteristics. An archetype denotes an average representation of the municipalities belonging to the cluster. The key archetypes selected for modeling are defined as those archetypes which represent the largest shares of national energy demand in the base year.

2.2 *Community Energy System Modeling Using TIMES*

The TIMES framework (Loulou et al. 2016) is utilized to develop a parameterized community energy systems model. This model is an abstract representation of a community, defined in terms of characteristic parameters (which are specified for each archetype via the clustering approach). Thus, the modeling framework can be readily adapted to represent different communities, enabling the evaluation of a wide range and large number of archetypes. This customizable formulation and application of a TIMES model is atypical, as TIMES models are traditionally designed to represent specific energy systems. TIMES energy models also traditionally represent large-scale energy systems (i.e., on a regional, national, or international level) (Goldstein and Tosato 2008; Gago da Camara Simoes et al. 2013; Amorim et al. 2014; Ramachandran and Turton 2016; Pattupara and Ramachandran 2016). The application of TIMES to develop community-scale models is less common.

The community model in this study minimizes the total system cost and provides details on capacity planning and dispatch over the modeling time horizon, from 2015 to 2050, for the set of technologies considered. Five-year time steps are utilized and end-use demands are modeled on an hourly basis for an average weekday and weekend across four seasons.

Model input parameters describe a single archetype community. Exogenous inputs to the community model reflect national NEP conditions until 2050. Inputs include a carbon tax, national grid electricity costs, fuel costs, efficiency improvements for end-use devices, and renovation potentials. Exogenous values are based on the NEP scenario described in (Kirchner et al. 2012) and results from the national Swiss TIMES model in (Ramachandran and Turton 2013). Overall, it is of interest to assess overarching trends and the collective CO_2 emissions reduction potential of the evaluated archetypes under NEP conditions; additional CO_2 constraints are not imposed.

End-use electricity and heat demands are determined according to national projections. End-use heat includes space heat, domestic hot water, and process heat across sectors. Hourly electricity demand is modeled by sector, while hourly heat demand is modeled by building category. Building categories include residential single and multi-family homes, commercial buildings, and industrial/agricultural buildings.

Technology investment options in the model relate to heat and electricity generation technologies, local storage, energy infrastructure, fuel conversion, renovation measures, and end-use devices. Local generation technologies in the electricity sector include rooftop photovoltaic (PV) panels, combined heat and power plants (small and micro CHP) for different fuel types (e.g., natural gas, wood, oil, and waste), and small hydro. Dedicated heat generation technologies include boilers (natural gas, wood, oil, electric, and waste-fueled), solar thermal panels, and air-source heat pumps, while storage includes building-level batteries and heat storage. Energy infrastructure includes electricity transmission and distribution grids, natural gas networks, and district heating networks. Gasification and processing technologies are utilized to convert biomass (wood, manure and waste) into biomethane or wood into pellets. Different renovation measures are also available, ranging from low to high cost options (e.g., window replacement to full building renovation). Electric end-use devices include five categories: lighting, cooking, refrigeration, cooling, and other appliances. Technology input data is primarily based on data applied in Swiss national energy system models, documented in (Ramachandran and Turton 2011, 2013, 2014; Panos and Ramachandran 2016). Cost and technology assumptions are further detailed in (Yazdanie 2017; Yazdanie et al. 2017).

3 Results

The archetypes defined using the clustering approach are described in the following text. The sections thereafter discuss archetype modeling results and technology trends with respect to heat and electricity demand under the NEP scenario.

3.1 Archetype Definition

The clustering approach yields more than 120 archetype groups (Fig. 1). The archetypes are ranked in order of their contribution to the total national energy demand; the 20 largest contributors are selected for subsequent cost optimization modeling.

Fig. 1 Geographic representation of archetype clusters selected for modeling

Each of the 20 archetypes is modeled using the TIMES community model. The modeling results for these archetypes represent approximately 80% of Swiss municipalities and (heat and electricity) energy demands. The selected archetypes and their contributions to the national energy demand are described in Table 1. Archetype modeling results are presented in the following sections.

3.2 *Heat Generation: Oil Substitution in All Archetypes*

The cost optimal heat generation mix over the modeling horizon across a range of archetypes is presented under the NEP scenario (Fig. 2). These archetypes have been selected in order to illustrate key trends and the diversity of observed results. The heat generation share across all 20 modeled archetypes in 2050 is provided in the Appendix.

The long-term generation mix differs notably between archetypes and is driven by differences in local energy infrastructure access and energy resource potentials. Natural gas forms a significant share of the heating mix in archetypes with access to the national gas network (for example, in Fig. 2a). Gas[1] technologies also provide a significant share of the heating mix in archetypes with access to relatively large biomass resources; in Fig. 2c, for instance, biomethane provides approximately

[1]Gas refers to methane from the natural gas network or to locally generated and delivered biomethane (or a combination of the two).

Table 1 Selected archetype details and modeling results

Arche-type ID	Archetype cluster characteristics			National energy share[b]	2050 DGT generation share using local resources		CO_2 emissions reduction in 2050 relative to 2015		
	DEC	ERP	EUS[a]		Heat (%)	Elec. (%)	Oil (%)	Gas (%)	Total (%)
1	Urban	High solar/ waste	Oil, com	6.2	25	12	97	0	97
2	Urban	High solar/ waste	Gas, com/ ind	29.1	29	19	53	21	74
3	Urban	High wood, med. solar	Gas, com/ ind	3.2	24	6	55	20	76
4	Rural	Low potentials, some hydro/ wood	Oil, res	2.0	95	59	100	0	100
5	Rural	Low potentials, some hydro/ wood	Oil, ind	2.3	71	22	100	0	100
6	Rural	Low potentials, some hydro/ wood	Oil, com	1.4	73	32	100	0	100
7	Rural	High solar/ waste	Oil, ind	3.6	49	14	96	0	96
8	Rural	High manure	Oil, ind	2.8	84	15	100	0	100
9	Rural	High wood, med. solar	Gas, com/ ind	1.5	59	15	55	27	83
10	Suburban	High solar/ waste	Oil, res	2.6	64	30	95	0	95
11	Suburban	High solar/ waste	Oil, com	2.2	38	17	97	0	97
12	Suburban	High manure/ waste	Oil, res	1.4	87	39	100	0	100
13	Suburban	High manure/ waste	Oil, ind	2.7	74	16	100	0	100
14	Suburban	High manure/ waste	Gas, com/ ind	4.0	55	17	55	33	88

(continued)

Table 1 (continued)

Arche-type ID	Archetype cluster characteristics			National energy share[b]	2050 DGT generation share using local resources		CO_2 emissions reduction in 2050 relative to 2015		
	DEC	ERP	EUS[a]		Heat (%)	Elec. (%)	Oil (%)	Gas (%)	Total (%)
15	Suburban	High waste	Oil, res	1.1	80	35	100	0	100
16	Suburban	High waste	Oil, ind	2.4	60	14	96	0	96
17	Suburban	High waste	Oil, com	1.2	65	19	100	0	100
18	Suburban	High waste	Gas, com/ind	4.1	48	16	55	28	84
19	Suburban	High manure	Oil, res	1.2	86	38	100	0	100
20	Suburban	High manure	Gas, com/ind	1.5	54	15	55	32	88

[a]Significant EUS fuel and sector; sector abbreviations: res (residential), com (commercial), ind (industry)
[b]National heat and electricity energy share represented by archetype results in the base year

50% of heat through gas technologies by 2050 (however, communities with relatively large biomass resources collectively represent a small share of the national energy demand). On average, across the evaluated archetypes, gas heating technologies generate approximately 20% of municipal heat in 2050.[2] Approximately 75% of the gas across these archetypes is sourced from the national gas network, while 15% is sourced from local manure and 10% is from municipal waste.

Archetypes which have limited access to gas (i.e., archetypes without national gas network access or insufficient local biomass resources to generate biomethane) rely more heavily on wood for heating. Wood replaces heating oil under the relatively high NEP scenario carbon tax. Only 2% of the heat generation mix is supplied by oil in 2050 on average across the considered archetypes under the NEP scenario.

Heat pumps generate a significant share of heat in 2050 across the archetypes, supplying up to 50% of municipal heating in 2050 (as observed in Fig. 2b). On average, across the modeled archetypes, heat pumps generate more than 35% of municipal heat in 2050.

By comparison, solar thermal technologies generate 13% of municipal heat in 2050 on average across the archetypes. Solar thermal heating plays a larger role in communities which have lower total ERPs relative to total demand and/or limited energy infrastructure access (for example, in Fig. 2b, d).

[2]Presented average figures are based on a weighted average considering archetype contributions to total national energy demand.

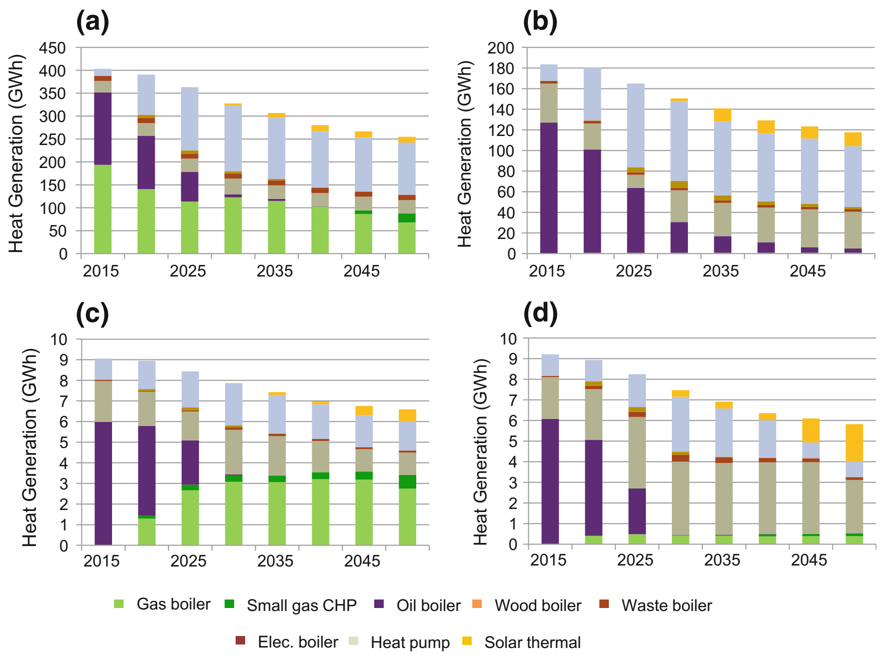


Fig. 2 Heat supply breakdown by technology over the modeling horizon under the NEP scenario for archetypes 3 (**a**), 1 (**b**), 12 (**c**), and 4 (**d**) (see Table 1 for archetype descriptions)

Building-level heat storage investments occur across all sectors. The operation of heat generation and storage technologies on a winter weekday in 2050 is illustrated exemplarily in Fig. 3 for archetype 1. In general, heat storage co-operates with solar thermal panels to store heat during the day and with heat pumps to store heat during low electricity price hours overnight. Heat is then discharged primarily during peak heat demand hours in the morning and evening, enabling peak shaving. The heat storage capacity represents between 5 and 14% of the heat demand during a winter weekday (i.e., the day with maximum heat demand over the year) in 2050 across the archetypes.

Renovation measures also play a vital role in reducing space heating demand over time. Renovations are largely deployed and enable the generation reduction observed over time in Fig. 2.

Local energy resources contribute significantly to local heat generation. On average, approximately 45% of heat generation is supplied by local ERPs in 2050 across the modeled archetypes (Fig. 4). Table 1 also provides the contribution of local resources to heat generation by modeled archetype. Solar, wood, and waste resources form the largest share of locally-sourced energy carriers for heating.

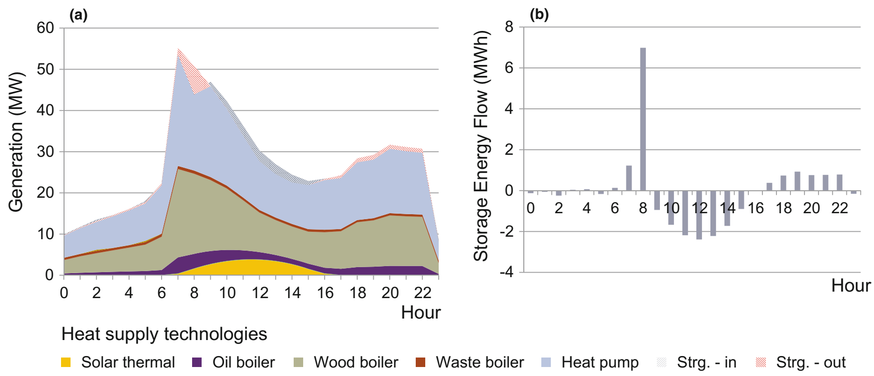


Fig. 3 Hourly heat supply by technology **a** and net storage flows **b** across all sectors on a winter weekday in 2050 in archetype 1 under the NEP scenario

3.3 Electricity Generation: The Emergence of Decentralized Generation

The electricity generation mix over the modeling horizon is presented for the same archetypes as in the preceding section (Fig. 5). The electricity generation share across all 20 modeled archetypes in 2050 is provided in the Appendix.

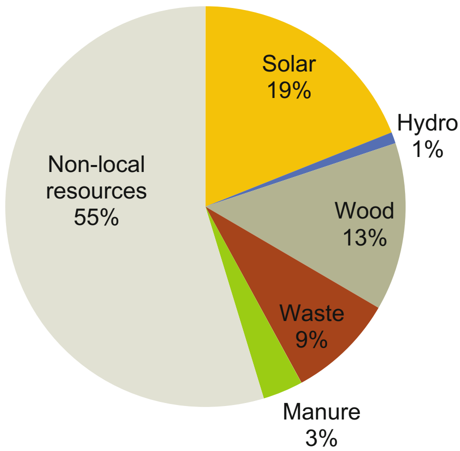
A range of supply mixes is observed across the archetypes. Communities rely on the national transmission network to meet the majority of electricity demand in most cases; however, decentralized generation technologies (DGTs) also provide a significant share of local electricity generation. National grid imports are reduced by 45% in 2050 compared to 2015, on average across the modeled archetypes. This result is driven by technology switching to DGTs and efficiency improvements in end-use technologies.

Solar PV panels generate approximately 15% of local electricity in 2050 across the modeled archetypes, on average. Small gas CHPs also contribute to local generation in communities where fuel is available (e.g., in Fig. 5a, c); these investments occur primarily in the industrial sector.

Small hydro potentials are generally available in small rural communities, such as the archetype in Fig. 5d. Small hydro plants are able to provide a significant share of local electricity generation in these archetypes; however, communities with similar small hydro potentials represent only 6% of national energy demand in the base year.

Battery storage investments occur across all sectors. The operation of electricity generation and storage technologies on a winter weekday in 2050 is illustrated exemplarily in Fig. 6 for archetype 1. In general, batteries store solar PV electricity during the day and grid electricity during low electricity price hours overnight. Batteries discharge largely during peak electricity demand hours in the evening.

Fig. 4 Heat generation by local energy resource in 2050, averaged across modeled archetypes, NEP scenario



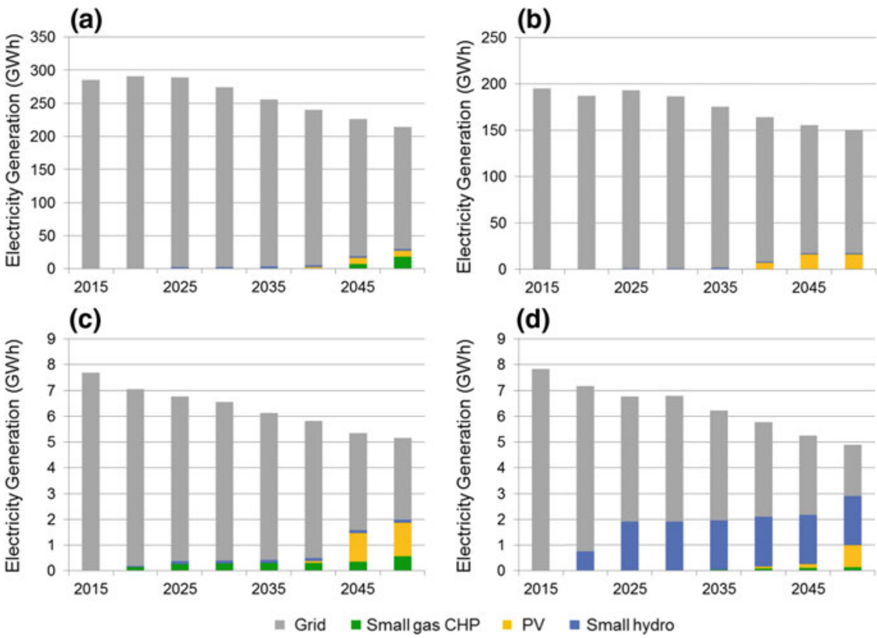


Fig. 5 Electricity supply breakdown by technology over the modeling horizon under the NEP scenario for archetypes 3 (**a**), 1 (**b**), 12 (**c**), and 4 (**d**) (see Table 1 for archetype descriptions)

The total battery capacity is equivalent to 7–11% of the total electricity demand during a winter weekday in 2050 across the modeled archetypes.

Local resources contribute significantly to municipal electricity generation in 2050. Approximately 20% of electricity is generated using local ERPs on average across the modeled archetypes in 2050, with solar PV providing the bulk of local

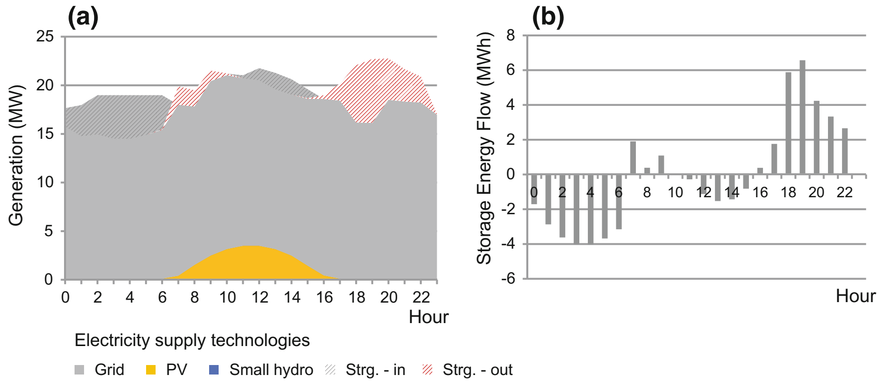
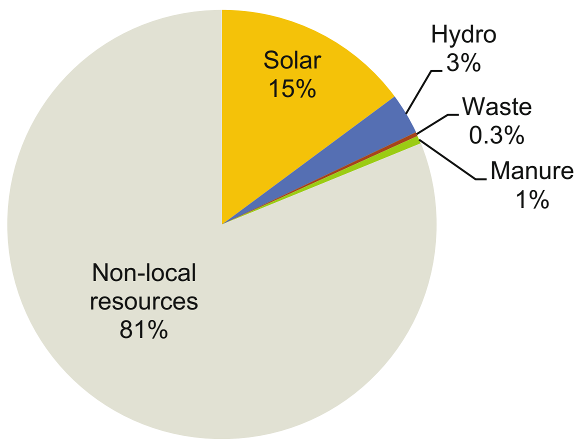


Fig. 6 Hourly electricity supply by technology **a** and net storage flows **b** across all sectors on a winter weekday in 2050 in archetype 1 under the NEP scenario

Fig. 7 Electricity generation by local and non-local energy resource in 2050, averaged across modeled archetypes under the NEP scenario



generation (Fig. 7). Table 1 details the contribution of local resources to electricity generation by modeled archetype.

3.4 CO_2 Emission Reductions: Over 95% for Most Archetypes

CO_2 emissions are evaluated for the combustion of fossil fuels within a community only. The implementation of high CO_2 taxes in the NEP scenario enables a drastic reduction in fossil fuel (i.e., oil and natural gas) usage across archetypes (Table 1). The majority of emission reductions are attributed to the reduced use of heating oil. The largest total reductions are observed for smaller rural and suburban archetypes, many of which demonstrate complete decarbonization of local heat and electricity generation in 2050 in the NEP scenario. Larger (e.g., urban) archetypes also demonstrate significant CO_2 emissions reductions, but continue to rely partially on fossil fuels (primarily natural gas) in order to meet large local demands that are not fully satisfied by local ERPs. The national gas network could be further decarbonized using biomethane in the future in order for these archetypes to achieve higher relative CO_2 emission reductions.

The CO_2 emissions reduction is 85% on average across the modeled archetypes in 2050 relative to 2015, with most archetypes demonstrating emission reductions of over 95%. This figure is even larger compared to 1990 levels; however, municipal-level data was not available for this year at the time of the study. Indicatively, national CO_2 emissions per capita were reduced by approximately 30% in 2015 compared to 1990 (The World Bank Group 2017). Overall, the average reduction meets Switzerland's targets within the Paris Agreement with respect to the evaluated sectors and archetypes.

4 Conclusion

Policymakers must employ a range of measures in order to achieve drastic global CO_2 emission reductions and limit the average global temperature increase to well within 2 °C this century. This set of measures must include local energy planning initiatives which focus on the deployment of decentralized generation and storage technologies, local renewable energy resources, and efficiency measures in the built environment.

This study presents an approach to evaluate a range of local energy systems within a larger region, enabling the identification of characteristic local energy system architectures and providing an adaptable cost optimization modeling framework to analyze key communities. The application of TIMES to develop this small-scale, parameterized community model differs from the conventional scope of TIMES models. The overall method is demonstrated for the Swiss case, but it can be adapted for different scales and evaluation criteria.

The proposed approach can be utilized by decision-makers ranging from the local to the international scale. The information gained using the method can inform the development and implementation of national policies that support local-scale decarbonization. The approach can also be employed by local policymakers to identify and encourage the uptake of suitable efficiency measures, DGSTs, and local ERPs.

Drastic reductions in local CO_2 emissions and energy demands are observed under the NEP scenario. The combustion of fossil fuels for local heat and electricity generation is reduced by 85% in 2050 relative to 2015, on average across the modeled key archetypes. This reduction exceeds Switzerland's CO_2 emissions reduction strategy in the context of the Paris Agreement, with respect to the evaluated archetypes and sectors. Several factors influence these results and should be considered by Swiss decision-makers at both the national and local level:

- Local-scale CO_2 emission reductions in the heating and electricity sectors in the long-term are driven largely by the implementation of relatively high CO_2 taxes.
- Space heating demand and CO_2 emission reductions are also driven by renovations in the building sector. As Switzerland's building sector currently accounts for over 40% of energy consumption and CO_2 emissions (Swiss Federal Office of Energy 2017), renovations must be encouraged by municipal governments in order to achieve ambitious climate targets.
- Several generation technologies and local energy resources facilitate the transition to low-carbon local energy systems as well, which should be supported by decision-makers. Heat pumps provide efficiency gains in the heating sector and form a significant part of the cost optimal heating mix by 2050. Local wood and waste resources, as well as solar thermal heating play an important role in decarbonizing the heating sector as well. Solar PV technologies form a key part of the decentralized electricity generation mix by 2050 across the modeled archetypes. PV, together with the adoption of energy-efficient end use devices, enables significant reductions in grid electricity demand by communities.

The aforementioned points should be considered as part of local climate policies. However, supplemental case-specific studies should also be developed in order to formulate individual municipal policies as the presented approach aims to identify key local archetypes and overarching trends. Still, the approach in this study provides policymakers with a powerful tool to assess local energy systems within a large region. The results of this work stress the value and importance of including local energy systems planning as part of national and international dialogues to mitigate climate change.

Appendix

The heat and electricity generation mix in 2050 across the modeled archetypes is illustrated in Figs. 8 and 9.

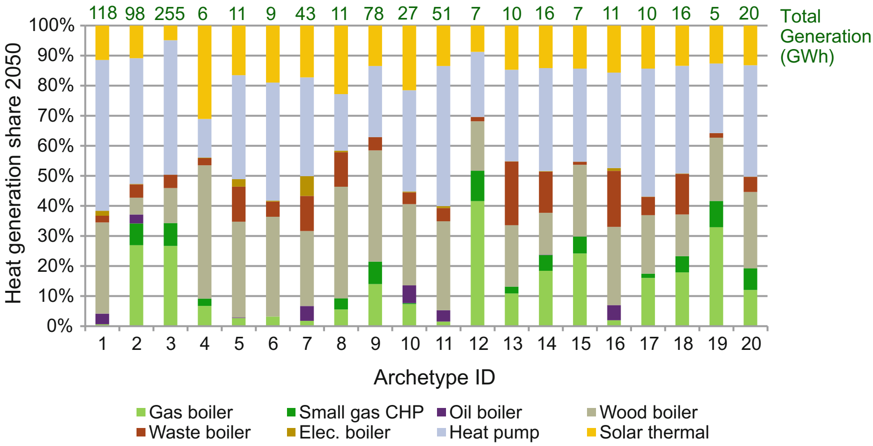


Fig. 8 Heat supply mix in 2050 across archetypes

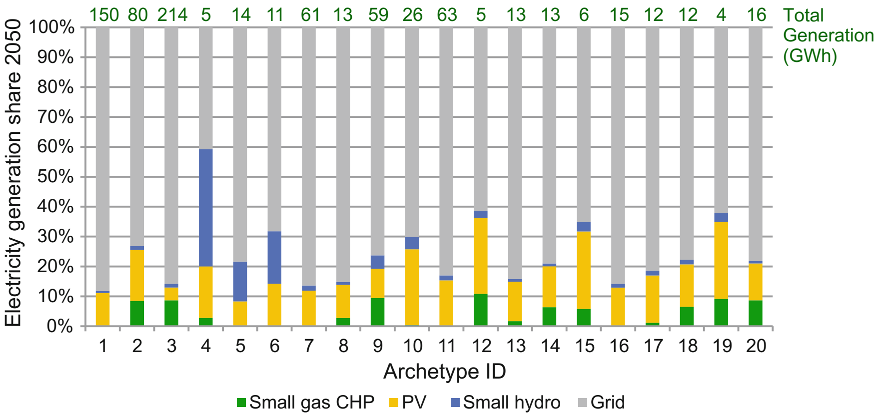


Fig. 9 Electricity supply mix in 2050 across archetypes

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