Exploring policy mixes for the decarbonization of the Swiss residential sector: a hybrid System Dynamics approach

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Abstract

The transition of the residential sector toward a low-carbon and energy-efficient future involves complex dynamics among technology diffusion, consumer behavior, and public policy. Traditional modeling approaches typically adopt either bottom-up or top-down perspectives, limiting their ability to simultaneously capture household heterogeneity and systemic feedbacks. This work presents a hybrid system dynamics model developed to explore policy mixes for the decarbonization of the Swiss residential sector. The model combines a detailed bottom-up representation of the building stock, segmented into thousands of archetypes, with a top-down description of system feedbacks affecting energy demand, emissions, and electricity generation. Within each archetype, the adoption of photovoltaic (PV) systems, heating technologies, and building envelope retrofits is modeled endogenously. An exploratory analysis based on a large ensemble of simulations is conducted by varying key policy instruments, including PV incentives, feed-in tariffs, CO_2 tax levels, the allocation of tax revenues between heating technologies and retrofits, and regulatory measures. Scenario outcomes are clustered to identify distinct transition pathways. Results highlight important trade-offs among policy objectives, showing that lower-emission and lower-consumption outcomes are more strongly associated with regulatory measures and higher CO_2 tax levels, while stronger PV incentives are associated with higher PV deployment but also with higher levy-related inequality.

1. Introduction

The transition of the residential sector toward a low-carbon and energy-efficient future is a complex socio-technical process shaped by technology diffusion, consumer behavior, and public policy [1]. Simulation models are therefore essential for exploring alternative policy scenarios and assessing their long-term implications for energy demand, emissions, and technology uptake [2]. Yet no single modeling approach is fully able to capture all relevant dimensions of this transition. Energy system optimization models are powerful for identifying efficient configurations, but they are less suited to representing the co-evolution of markets, technologies, institutions, and household decisions. More broadly, simulation approaches to residential energy transitions have historically developed along two main lines, bottom-up and top-down, each offering important insights while also exhibiting important limitations when used in isolation [3].

Bottom-up models, especially agent-based models (ABM), represent the decisions and interactions of individual actors or groups [4, 5]. They are well suited to capturing the heterogeneity of buildings and households, and to linking technology adoption to behavioral, social, economic, and spatial factors [6]. Such models have been widely applied to the diffusion of photovoltaic (PV) systems [7, 8], heat pumps [9], electric vehicles [10], and building retrofits [11]. However, they often treat the broader energy system as static or exogenous. Electricity prices, emissions, and policy conditions are frequently imposed by the modeler rather than generated endogenously, which limits the ability of these models to capture systemic feedbacks between individual adoption decisions and macro-level outcomes.

Top-down models adopt the opposite perspective, focusing on aggregate relationships among variables such as total energy demand, installed capacities, prices, and emissions. System dynamics (SD) modeling belongs to this family and is particularly useful for analyzing feedback structures, time delays, and nonlinear behavior in long-term transitions [12]. SD models are therefore well suited to studying how reinforcing and balancing feedback loops shape the evolution of energy systems over time. Their main weakness is the loss of granularity: the diversity of buildings, households, and local contexts is usually collapsed into few representative averages. As a result, top-down models are less able to reflect the heterogeneity and behavioral complexity that drive the adoption of residential energy technologies.

Recent research has increasingly turned to hybrid approaches that aim to combine the strengths of bottom-up and top-down modeling [13, 14]. Such approaches make it possible to represent heterogeneous adoption processes at the micro level while also capturing the systemic feedbacks that emerge at the aggregate level. This is particularly relevant in the residential sector, where policy outcomes depend not only on the characteristics

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of individual buildings and households, but also on how adoption patterns affect electricity demand, prices, emissions, and the public resources available to support further diffusion.

Against this background, this paper introduces a hybrid system dynamics model to explore alternative policy pathways for the decarbonization of the Swiss residential sector. Switzerland provides a relevant case study because of its ambitious climate and energy targets [15], its high relevance of residential heating emissions, and its institutional setting in which multiple policy instruments coexist across federal and cantonal levels. The proposed model combines a bottom-up representation of residential building-stock heterogeneity with a top-down representation of system-level feedbacks. The building stock is segmented into thousands of archetypes, each representing a subset of buildings with similar physical and geographical characteristics. Within each archetype, the adoption and replacement of key technologies are modeled endogenously, including PV systems, heating technologies, and building-envelope retrofits. At the same time, the model captures how these decentralized decisions aggregate into macro-level outcomes such as electricity demand, final energy use, emissions, and electricity prices, which in turn feed back into future adoption decisions through changes in costs, incentives, and public budgets.

This integrated perspective is important for two reasons. First, residential decarbonization involves the simultaneous diffusion of multiple technologies whose effects are interdependent. PV deployment, heat pump adoption, and retrofit decisions influence each other through energy costs, self-consumption and heating demand. Analyzing these technologies in isolation can therefore lead to incomplete or misleading conclusions, especially when several policy instruments are applied at the same time [16]. Second, the effects of policy instruments depend not only on their direct incentives, but also on how they are financed and how they interact over time. In practice, taxes, subsidies, levies, and regulations do not operate independently. They form policy mixes whose combined effects may reinforce or counteract each other [17, 18, 19].

The paper addresses three related research questions. First, which policy instruments and policy combinations are most strongly associated with lower cumulative CO_2 emissions and lower final space-heating demand in the Swiss residential sector? Second, which policy instruments are most effective in accelerating PV deployment, and what trade-offs do they create in terms of distributional inequality? Third, to what extent do policy financing mechanisms and the allocation of CO_2-tax revenues shape transition outcomes compared with regulatory measures and tax levels themselves?

To answer these questions, the model is used in an exploratory analysis based on a large ensemble of simulations in which policy instruments and uncertain parameters are varied jointly [20, 21, 22]. The resulting scenario ensemble is then analyzed to identify recurring outcome patterns and the trade-offs associated with different policy mixes. In this way, the paper moves beyond single-policy scenario comparison and instead examines how combinations of instruments shape decarbonization, energy efficiency, technology deployment, and distributional outcomes under uncertainty.

Taken together, this work contributes to the field of residential energy transition modeling in two ways:

i) it integrates discrete-choice adoption of PV, heating systems, and retrofit decisions across 8,580 building archetypes with endogenous feedbacks linking electricity pricing, policy financing, and technology diffusion;
ii) it uses exploratory simulations and clustering to identify recurring outcome patterns and to quantify the trade-offs between decarbonization, PV deployment, energy efficiency, and distributional impacts across alternative policy mixes.

The analysis yields four main findings. First, regulatory measures and higher CO_2 tax levels are strongly associated with lower cumulative emissions. Second, stronger PV incentives increase installed PV capacity, but are also associated with higher inequality in the distribution of levy-related costs and benefits. Third, the funding structure of policy support plays a central role in shaping distributional outcomes, indicating that policy design matters not only through incentive levels but also through who ultimately pays for them. Fourth, the interaction between heating-technology adoption and building-retrofit decisions generates system effects that would be difficult to capture in isolated single-technology or single-policy analyses.

The rest of the paper is structured as follows: Section 2 presents the model structure and the exploratory analysis; Section 3 discusses the results; Section 4 outlines the main limitations and directions for future work; finally, Section 5 concludes.

2. Methodology

This section describes the structure of the model and the exploratory analysis used to evaluate alternative policy configurations for the Swiss residential energy transition. The framework combines a disaggregated representation of the residential building stock with system-level feedbacks linking technology adoption, electricity demand, prices, emissions, and public support schemes.

2.1. System Dynamics model overview

The System Dynamics model used in this study builds on the modeling framework previously developed in [23, 24, 25]. Figure 1 summarizes the main structure of the model. The left side reports the input data and assumptions, the right side the outputs used to assess policy-mix performance, and the center the main model components and feedback loops linking them. At the micro level, households decide whether to adopt PV, replace heating systems with alternative technologies, and improve the thermal performance of the building envelope (Sections 2.3.2, 2.3.1, and 2.3.3, respectively). At the macro level, the aggregation of these decisions affects grid electricity demand, sectoral final energy use, and residential sector CO_2 emissions. These aggregate outcomes feed back into future adoption decisions through changes in electricity prices (Section 2.4.1), public support schemes, and their funding mechanisms.

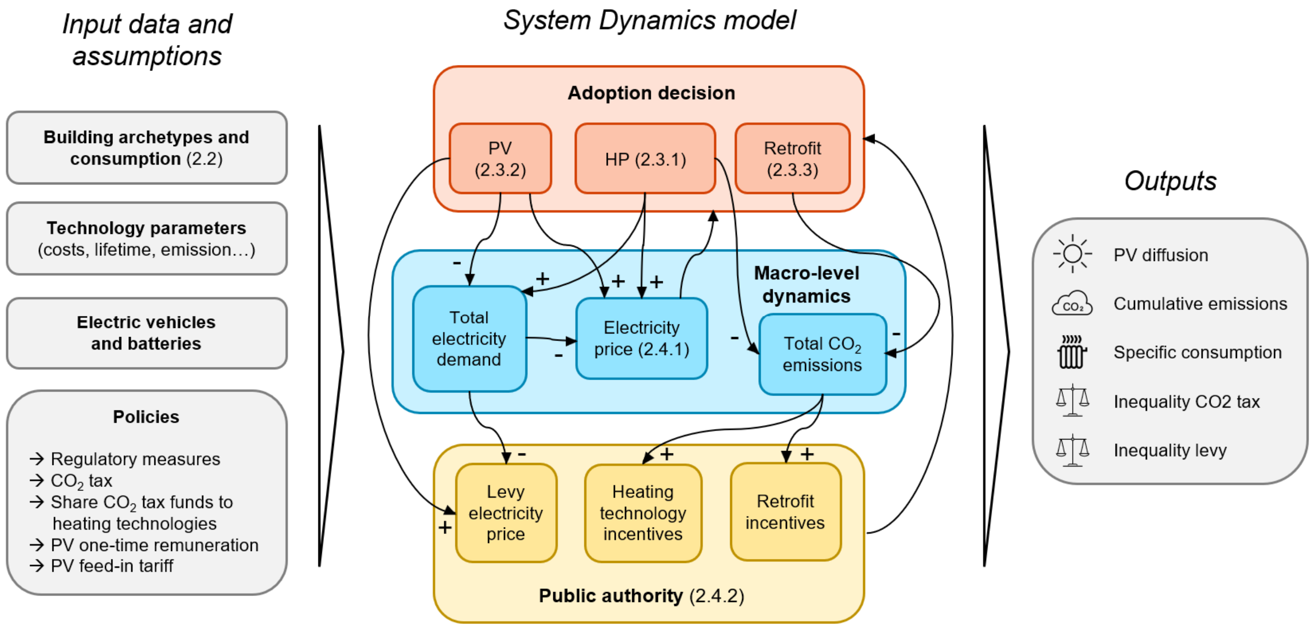

Figure 1: Graphical representation of the main steps involved in the framework and of the main modules of the developed model.

Several feedback structures are central to the analysis. First, higher PV adoption reduces grid demand through self-consumption and may trigger a so-called "death spiral" mechanism [26]. Since a large share of electricity-utility costs are fixed, lower electricity demand from the grid can increase retail tariffs, which in turn improves the economic attractiveness of PV and further accelerates its adoption. Second, higher diffusion of renewable heating systems and retrofits reduces fossil fuel use, which lowers CO_2 tax revenues and therefore affects the future subsidy budget available to support further adoption. Third, heat pump diffusion reduces operating costs for space heating, which may weaken the economic attractiveness of deep envelope retrofits. Fourth, peer effects reinforce the diffusion of PV and heating technologies across building archetypes. In addition, the model accounts for grid-reinforcement costs associated with higher distributed generation and electrification. These developments may require utilities to reinforce the grid in order to avoid voltage and ampacity violations, and the resulting costs are recovered through electricity tariffs [27]. At the same time, heat pump diffusion increases electricity demand from the grid and may partly offset the reduction caused by higher PV self-consumption, contributing to lower electricity prices in the long term. In this way, the model links household decisions, policy design, and system-wide outcomes within a single endogenous framework.

Micro-level decisions and macro-level system dynamics are further connected through the explicit representation of public authority behavior. Unlike technology-diffusion models that treat policy support as exogenous, the model represents feedbacks between technology uptake, electricity levies, CO_2-tax revenues, and available subsidy budgets. Drawing on the Swiss policy context, PV support is represented as being financed through a levy on electricity consumption [28], while support for renewable heating technologies and building retrofits is represented as being financed through revenues from a federal CO_2 tax on oil and gas imports [29]. These mechanisms close additional feedback loops that influence both future adoption decisions and aggregate system outcomes.

2.2. *Residential building archetypes and consumption*

The residential building stock is represented through archetypes rather than individual buildings. This choice preserves heterogeneity while keeping the model computationally tractable for exploratory analysis. Building-level information was assembled by combining three public datasets: (*i*) the Register of Buildings and Dwellings, which provides information on building type, heating system, size, and number of dwellings [30]; (*ii*) the Swiss electricity production plants database, which reports plant location, capacity, and installation year [31]; and (*iii*) the roofs suitability to solar power dataset, which provides the technical suitability and electricity-generation potential of roof surfaces [32]. The spatial integration of these datasets yields a harmonized database of Swiss residential buildings.

Buildings are then grouped by canton, building type, thermal-efficiency, PV presence, and heating solution, resulting in 8,580 possible archetypes. Each archetype represents a subset of buildings with similar physical, technical, and geographical characteristics, and constitutes the unit on which adoption decisions are simulated. Space-heating demand is estimated for each archetype using a hybrid bottom-up/top-down procedure. Mean specific consumption values by canton, building type, and construction period [33] are combined with national energy statistics [34] to ensure consistency between the disaggregated representation of the stock and aggregate residential heating demand. Further details on the data integration procedure are reported in [23, 25].

2.3. Endogenous household decisions

2.3.1. HP adoption

Heating system decisions are modeled as replacement choices that occur when the existing system reaches the end of its lifetime. For each archetype, households choose among the feasible heating options using a Multinomial Logit specification [35]. The set of alternatives includes oil, gas, wood, pellet, direct electric heaters, heat pumps, and hybrid configurations combining space-heating technologies with solar thermal for domestic hot water.[1]

The choice set is first filtered according to cantonal regulations [36], as well as district-heating and gas-grid availability [37]. For each archetype i, year t, and available heating technology j, the number of new installations is given by:

$$I^{HS}_{j,i,t} = BC_{i,t} \cdot \rho^{HS}_{j,i,t} \tag{1}$$

where $BC_{i,t}$ is the number of buildings replacing their heating system, assumed to occur at the end of the system lifetime, and $\rho^{HS}_{j,i,t}$ is the probability of choosing option j:

$$\rho^{HS}_{j,i,t} = \frac{\exp(\lambda^{HS}_{j,i,t})}{\sum_j \exp(\lambda^{HS}_{j,i,t})} \tag{2}$$

The perceived utility $\lambda^{HS}_{j,i,t}$ depends on techno-economic and behavioral attributes, including investment and operating costs, peer effects, PV presence, income, building value, and a dummy for hybrid solar-thermal solutions [23, 25]. The resulting heating-technology mix affects both fossil fuel use and electricity demand, and therefore plays a central role in the model's emissions and electricity price dynamics.

2.3.2. PV adoption

PV adoption is modeled as a binary decision using a logit specification [38]. For each archetype i and year t, the annual number of installations is:

$$I^{PV}_{i,t} = B_{i,t} \cdot \rho^{PV}_{i,t} \tag{3}$$

where $B_{i,t}$ is the number of eligible buildings:

$$B_{i,t} = B^{TOT}_{i,t} \cdot \epsilon_i - B^{PV}_{i,t} \tag{4}$$

Here, $B^{TOT}_{i,t}$ is the total stock of buildings in archetype i, ϵ_i is the share of technically suitable buildings [32], and $B^{PV}_{i,t}$ is the number of buildings already equipped with PV. Adoption probability follows a logit formulation:

$$\log\left(\frac{\rho^{PV}_{i,t}}{1-\rho^{PV}_{i,t}}\right) = \lambda^{PV}_{i,t} \tag{5}$$

where the perceived utility of adoption is defined as:

$$\lambda^{PV}_{i,t} = \alpha + \sum_k \beta_k \cdot att_{i,t} + \gamma_i \tag{6}$$

The perceived utility $\lambda^{PV}_{i,t}$ depends on peer effects, economic attractiveness, income, heat pump presence, and building value [23, 25]. PV adoption affects grid electricity demand through self-consumption and also influences the levy used to finance PV support. This creates an endogenous feedback between diffusion, electricity-related costs, and future adoption incentives.

2.3.3. Building envelope retrofit decisions

Envelope retrofit decisions are modeled when major building components (roof, wall and ground) reach the end of their lifetime. At that point, households may either preserve the current thermal efficiency level or upgrade to a more efficient category. The model distinguishes five efficiency levels and uses a Multinomial Logit specification to represent transitions between them. For each archetype i, year t, initial efficiency level k, and destination level j, the number of buildings moving to level j is:

$$R_{j,i,t} = \sum_k \left(BC_{k,i,t} \cdot \rho^{R}_{k,j,i,t}\right) \tag{7}$$

where $BC_{k,i,t}$ denotes the number of buildings in level k undergoing component replacement at the end of the component lifetime, and $\rho^{R}_{k,j,i,t}$ is the probability of choosing level j:

$$\rho^{R}_{k,j,i,t} = \frac{\exp(\lambda^{R}_{k,j,i,t})}{\sum_j \exp(\lambda^{R}_{k,j,i,t})} \tag{8}$$

The utility $\lambda^{R}_{k,j,i,t}$ reflects the trade-off between higher investment costs for better insulation and the discounted value of future energy savings [39]. Retrofit decisions directly affect final heating demand and indirectly interact with heating-system adoption by changing the energy required for space heating.

2.4. System-level feedbacks

2.4.1. Electricity price

Electricity prices are represented through a stylized formulation designed to capture the long-term feedbacks relevant for technology adoption. For simplicity, each canton is represented by a single distribution system operator (DSO). Electricity prices are driven by three main factors: (*i*) grid-reinforcement costs required to accommodate increasing distributed generation and consumption electrification, (*ii*) changes in total annual electricity demand delivered through the grid, and (*iii*) the federal levy used to finance PV support. Retail electricity prices include an energy component, transmission and distribution charges, cantonal taxes, and the federal levy:

$$p = e_p + c_{TSO} + c_{DSO} + t_c + l \tag{9}$$

where e_p is the energy price, c_{TSO} the transmission system operator charge, c_{DSO} the distribution system operator charge, t_c a cantonal tax, and l the federal levy. c_{DSO} is represented as:

$$c_{DSO} = \frac{Cost}{Demand} \tag{10}$$

[1] The hybrid options include a technology used for space heating combined with solar thermal collectors for domestic hot water production. The OilST, GasST, HPST, and WoodST solutions assume oil, gas, heat-pump, and wood-based space-heating systems, respectively, combined with solar thermal for domestic hot water.

where *Cost* denotes total annual distribution costs and *Demand* the electricity delivered by the DSO. In this formulation, lower grid demand increases the distribution charge if fixed costs remain unchanged, while additional grid-reinforcement costs associated with PV, heat pumps, and electric vehicles further increase distribution costs [27, 40]. Historical values of demand and c_{DSO} are used to initialize the model and estimate initial DSO costs. While base grid costs are assumed constant in real terms, additional grid-upgrade costs associated with PV, heat pump, and electric vehicle penetration are incorporated at the cantonal level. The transmission system operator charge is assumed to increase by 1% annually in real terms. This mechanism allows the model to capture how decentralized electrification and self-generation affect future electricity prices.

2.4.2. Public authority behavior and policy financing

The model explicitly represents the funding mechanisms of the two main support schemes considered in the analysis. PV support is represented as being financed through a levy on electricity consumption [28], while support for renewable heating technologies and building retrofits is represented as being financed through revenues from a federal CO_2 tax on fossil fuels, consistent with the Swiss policy context [29].

The electricity levy changes endogenously to recover the cost of PV support granted during the preceding period, based on observed electricity demand over the same period. To reflect political inertia and policy cycles, the levy is not updated annually, but every five years. This creates a delayed feedback between PV uptake, the budget required to support it, and the levy paid by electricity consumers. The levy, which was set at 0.45 Rp/kWh in 2008, has gradually increased to 2.3 Rp/kWh and is applied uniformly to all electricity consumers. In parallel, the CO_2 tax level is treated as an exogenous policy input, whereas the subsidy budget available for heating systems and retrofits evolves endogenously with the revenues generated by fossil fuel use. As renewable heating technologies and retrofits spread, the tax revenues shrink, reducing the future resources available for the same support schemes.

The model also reflects the institutional distinction between federal and cantonal levels in the Swiss policy framework. While legislative authority over electricity support lies at the federal level, building energy regulation rests with the cantons (Art. 89 [41]). Consequently, subsidies for renewable heating and building retrofits vary across cantons [42], while the CO_2 tax rate itself is treated as a federal policy input. The revenues generated by the tax are redistributed to cantons proportionally to their population. Within the available budget, the share allocated to heating systems versus retrofits is represented as a policy variable. This representation makes it possible to assess not only the effect of incentive levels, but also the consequences of their funding structure and internal allocation for long-term technology adoption and distributional outcomes.

2.5. Exogenous drivers and scenario assumptions

The model endogenizes PV adoption, heating-system replacement, retrofit decisions, electricity demand, electricity prices, and policy feedbacks. Other drivers are represented exogenously. In particular, the diffusion of electric vehicles and stationary batteries is imposed through external trajectories derived from official statistics and observed adoption rates [15, 43]. These technologies affect electricity demand and self-consumption, but their adoption is not modeled as a household choice in the present version.

Five policy inputs are varied in the exploratory analysis:

- PV one-time remuneration: modeled as a federal investment grant covering a share of PV installation costs, with levels set at 0%, 20% (approximately the current Swiss level), and 40%.

- PV feed-in tariff: in Switzerland, surplus electricity not self-consumed is sold to the local DSO at the weighted average market energy price [44]. The feed-in tariff considered here, which is not currently in place, is modeled as an additional remuneration on top of the market-based payment. The levels analyzed are 0 CHF/kWh, 0.05 CHF/kWh, and 0.10 CHF/kWh.

- CO_2 tax: three levels are considered: 0 CHF/tCO_2, 120 CHF/tCO_2 (currently in force), and 240 CHF/tCO_2.

- Allocation of CO_2 tax revenues between heating technologies and retrofits: as described in Section 2.4.2, revenues from the CO_2 tax are used to finance incentives for renewable heating systems and building retrofits. This policy variable represents the share of total funds allocated to heating technologies, with levels set at 25%, 50% (approximately the current allocation), and 75%.

- Regulatory measures: Switzerland has adopted two versions of the Cantonal Model of Energy Prescriptions for buildings (2014 [36] and 2025 [45]), which include measures such as bans on purely fossil heating systems and direct electric heating. The presence of these regulatory frameworks is represented as a binary input in the model.

For the policy inputs, each scenario is generated by random sampling from categorical distributions that assign equal probability to each discrete policy level. In addition, key techno-economic parameters for PV and heating technologies, including cost, performance or efficiency, and lifetime, are sampled from uniform distributions within the ranges reported in Appendix B.

2.6. Exploratory analysis design

Once calibrated and validated with historical data (Appendix A; [23, 25]), the model is used to explore how the Swiss residential sector may evolve under alternative policies and uncertain future input values. Historical values are maintained up to 2025, after which the sampled policy settings and uncertain parameters determine the simulated trajectories. In total, 1,500 simulation runs are performed varying policy inputs and uncertain techno-economic parameters.

The analysis focuses on five outputs selected to reflect the main policy dimensions addressed in the paper: (*i*) cumulative residential sector CO_2 emissions over 2025-2050, (*ii*) installed PV capacity in 2050, (*iii*) average specific space heating demand in 2050, (*iv*) inequality (measured with the Gini coefficient) in levy related net contributions, and (*v*) inequality (measured with the Gini coefficient) in CO_2 tax related net contributions. PV capacity is included because PV is regarded as a key technology in Switzerland for replacing electricity currently generated by nuclear power plants following the national phase-out decision. Average specific space-heating demand is included because of its central role in the Swiss energy strategy. The two inequality indicators measure the distribution of net policy incidence across residential segments. The Gini coefficient is computed across segments defined by the combination of canton and building type. For each segment, net contributions are computed as payments through the levy or the CO_2 tax over the transition period minus the incentives received through the corresponding support scheme; the resulting net contributions are then compared using the absolute Gini coefficient.

To support interpretation of the large scenario ensemble, simulation outputs are standardized and clustered using the K-means algorithm. Clustering is used here to identify recurring outcome patterns across scenarios, rather than to infer causal effects of individual policies. Based on silhouette analysis and interpretability, a solution with $k = 10$ clusters is retained (Appendix C). To enable a more detailed discussion, five clusters are then selected for further interpretation. The selection is based on the geometric distance between cluster centroids in the standardized five-dimensional outcome space, with the aim of covering qualitatively distinct combinations of emissions, PV deployment, energy efficiency, and distributional outcomes. This facilitates the interpretation of distinct outcome configurations and of the policy combinations most frequently associated with them. Overall, this methodology makes it possible to examine how alternative policy mixes shape recurring outcome patterns under uncertainty, while keeping explicit the feedbacks linking technology diffusion, prices, public budgets, and distributional effects.

3. Results

Figure 2 provides an overview of the 1,500 simulated scenarios across the five outputs of interest. The scenario ensemble spans a wide range of outcomes: installed PV capacity in 2050 varies between about 8 and 25 GW, cumulative residential sector CO_2 emissions over 2025-2050 range from about 45 to 85 $MtCO_2$, and average specific space heating demand in 2050 lies between about 57 and 67 kWh/m^2y. The two inequality indicators also display substantial variability, with levy related inequality ranging approximately from 0.15 to 0.75 and CO_2 tax related inequality from about 0.20 to 0.25. The figure already highlights the presence of trade-offs in the residential transition, as no single region of the simulated outcome space performs best across all five indicators simultaneously.

Figure 3 reports the average performance of the five indicators for each cluster and shows that the clusters occupy markedly different regions of the outcome space. Some clusters perform relatively well across multiple dimensions, but none simultaneously dominates on all five indicators. For example, cluster 3 combines comparatively low cumulative emissions, low specific consumption, and low inequality associated with both the levy and the CO_2 tax. However, the same cluster performs comparatively poorly in terms of installed PV capacity. More generally, the cluster averages confirm that improvements in one policy objective are often associated with weaker performance in at least one of the others. To support a more detailed interpretation, five clusters were selected from the ten identified clusters by maximizing the minimum geometric distance among cluster centroids in the five-dimensional outcome space. This procedure led to the selection of clusters 0, 1, 2, 3, and 5. These clusters, shown in Figure 4, should be interpreted as illustrative outcome areas within the broader simulated ensemble, while Figure 5 shows the policy configurations most frequently associated with them.

A first robust pattern concerns cumulative emissions and final specific space heating demand. Across the selected clusters, lower emission outcomes are more frequently associated with the presence of regulatory measures and with higher CO_2 tax levels than with changes in the internal allocation of CO_2 tax revenues. Regulatory measures appear to be particularly important for emissions: clusters 1 and 5, in which almost all simulated scenarios include regulatory measures, exhibit lower cumulative emissions than clusters 0 and 2, where such measures are largely absent and emissions are higher. At the same time, regulatory measures do not appear to have a comparably strong effect on installed PV capacity. For instance, cluster 5 combines low PV deployment with the presence of regulatory measures, whereas cluster 2 combines the absence of regulatory measures with moderately high PV capacity. This suggests that, in the present model, regulatory measures mainly affect the decarbonization of heating rather than the deployment of PV.

Regulatory measures also appear to influence final specific energy consumption, although more weakly than emissions. This is illustrated by the comparison between clusters 0 and 5. These clusters have relatively similar distributions of most policy inputs except for regulatory measures, yet they differ not only in cumulative emissions but also slightly in final specific space-heating demand. A plausible mechanism is that the diffusion of efficient heating technologies such as heat pumps lowers operating costs for space heating through higher system efficiency. This, in turn, may reduce the economic attractiveness of deep building envelope retrofits, leading to a slight increase in final specific heating demand. Although this effect should be interpreted with some caution, the pattern is consistent with an interaction between heating technology efficiency and renovation incentives.

Higher CO_2 tax levels are also associated with lower final specific space heating demand. This is particularly visible when comparing clusters 0 and 2, which show a broadly similar distribution of regulatory measures but differ in the prevalence of CO_2 tax levels, with lower tax values more common in cluster 0 and higher values more common in cluster 2. A higher CO_2 tax increases variable heating costs, thereby improving the eco-

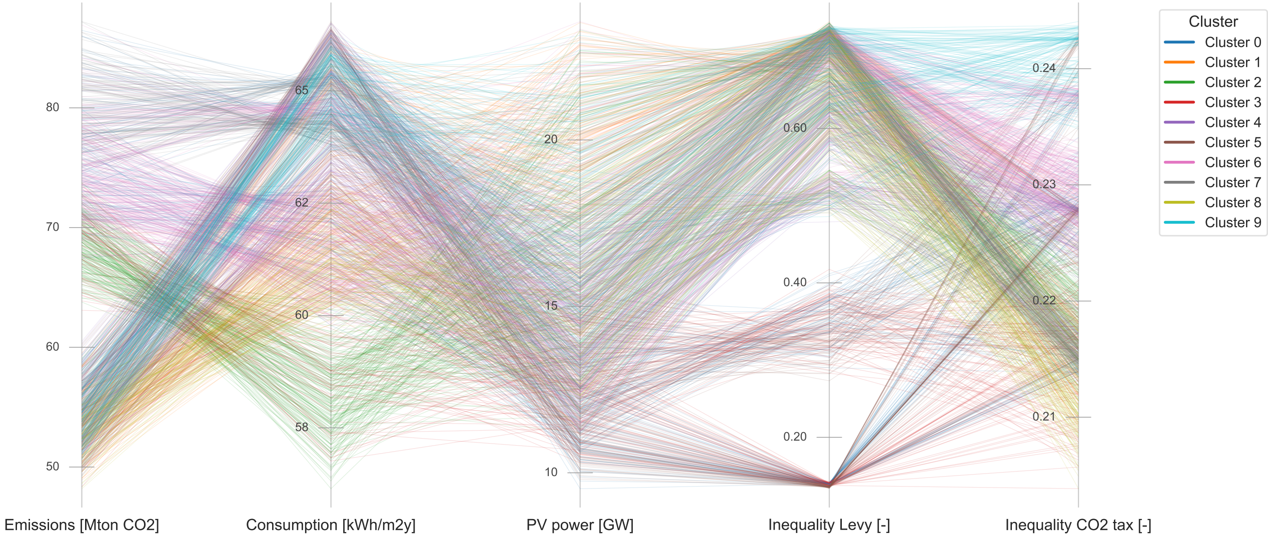

Figure 2: Exploratory analysis results for the five outputs of interest across the simulated policy and uncertainty configurations, shown as a parallel-coordinates plot and colored by cluster membership.

Cluster	PV power [GW]	Emissions [Mton CO2]	Consumption [kWh/m2y]	Inequality CO2 tax [-]	Inequality levy [-]
0	11.8	76.2	63.0	0.226	0.256
1	20.1	53.7	63.0	0.219	0.710
2	16.9	68.6	58.2	0.218	0.664
3	12.5	60.7	60.1	0.214	0.266
4	14.5	54.7	64.7	0.224	0.616
5	12.0	54.5	65.1	0.230	0.232
6	16.0	74.7	62.1	0.231	0.659
7	16.4	80.1	64.5	0.215	0.659
8	14.9	53.0	61.2	0.211	0.633
9	17.2	54.4	65.1	0.240	0.662

Legend: Better, Average, Worse

Cluster	PV power [GW]	Emissions [Mton CO2]	Consumption [kWh/m2y]	Inequality CO2 tax [-]	Inequality levy [-]
0	11.8	76.2	63.0	0.226	0.256
1	20.1	53.7	63.0	0.219	0.710
2	16.9	68.6	58.2	0.218	0.664
3	12.5	60.7	60.1	0.214	0.266
4	14.5	54.7	64.7	0.224	0.616
5	12.0	54.5	65.1	0.230	0.232
6	16.0	74.7	62.1	0.231	0.659
7	16.4	80.1	64.5	0.215	0.659
8	14.9	53.0	61.2	0.211	0.633
9	17.2	54.4	65.1	0.240	0.662

Legend: Low, Average, High

Figure 3: Summary of the five outputs of interest for the ten identified clusters. For each output, the five best- and worst-performing clusters are highlighted according to either raw magnitude or desirability.

nomic attractiveness of building retrofits. At the same time, it generates additional revenues that can be redistributed as incentives for renovation, further stimulating improvements in the thermal envelope. For similar reasons, higher CO_2 tax levels are also associated with lower cumulative CO_2 emissions: they improve the profitability of renewable heating technologies while increasing the funds available to support their adoption.

By contrast, the internal allocation of CO_2 tax revenues between heating technologies and retrofits appears to have a comparatively smaller effect on emissions and final specific consumption than either the presence of regulatory measures or the overall level of the CO_2 tax. For example, clusters 0, 2, and 5 display similar distributions of the heating-versus-retrofit allocation variable across its three tested levels, yet they differ substantially in cumulative emissions and average specific heating demand. This suggests that, within the present scenario ensemble, the overall strength of carbon pricing and the presence of regulatory constraints play a more decisive role than the precise redistribution of the corresponding subsidy budget.

A second clear pattern concerns the relationship between PV deployment and levy related inequality. Higher levels of PV one-time remuneration and feed-in tariffs are more frequently associated with clusters characterized by high installed PV capacity. This is evident when comparing clusters 0, 3, and 5, which are more often associated with lower PV support levels and lower installed PV capacity, with clusters 1 and 2, where stronger PV incentives are more prevalent and PV deployment is higher. However, strong PV incentives are also associated with a higher likelihood of belonging to clusters with elevated levy related inequality. The trade-off between PV capacity and levy-related inequality is already visible in Figure 2 and is further supported by the comparison between Figures 4 and 5. This trade-off emerges from the joint effect of three mechanisms represented in the model. First, stronger PV incentives increase the financial support received by PV adopters. Second, self-consumption reduces the contribution of prosumers to the levy base. Third, higher support levels induce higher levy adjustments by public authorities in order to recover policy costs. Together, these mechanisms shift a larger share of the financing burden onto non-adopters, thereby increasing inequality in

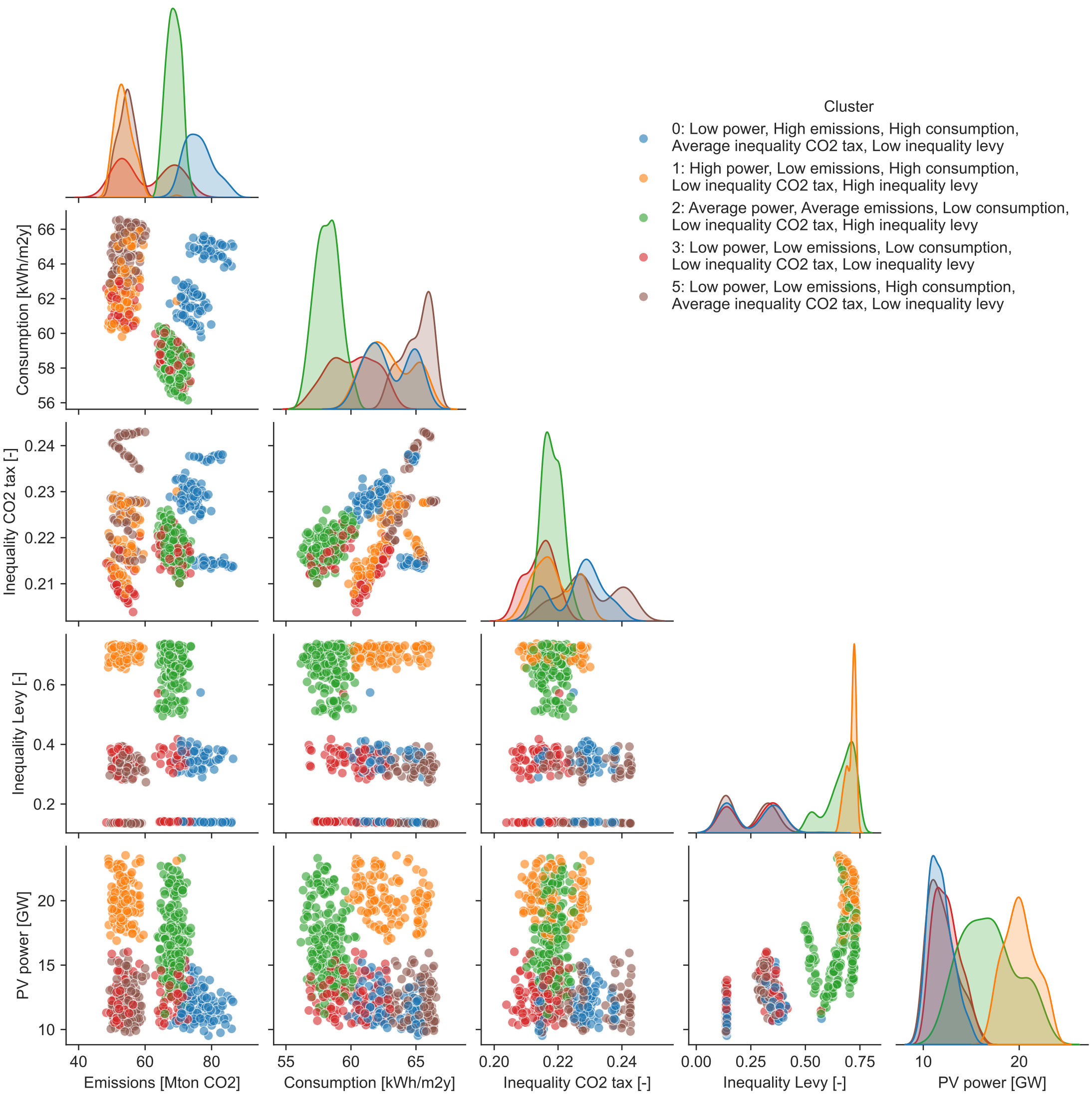

Figure 4: 2D representation of the performance of the selected five clusters in the outputs of interest.

levy-related net contributions. In this sense, the results suggest that PV-support policies are effective in accelerating deployment, but they also generate a structural trade-off through the way they are financed.

The distributional implications of CO_2 tax funded support differ from those associated with the electricity levy. Higher CO_2 tax levels are associated with lower emissions and lower final specific heating demand, but not necessarily with a marked increase in CO_2 tax related inequality. In contrast to the levy mechanism, where non-adopters partly finance benefits accruing to adopters, the CO_2 tax is paid primarily by users of fossil heating systems, who are also the main potential beneficiaries of heating and retrofit support. As a result, higher CO_2 tax levels do not automatically exacerbate inequality to the same extent observed for levy funded PV support. This difference between the two inequality indicators highlights that the distributional incidence of a policy depends not only on its intensity, but also on its funding design.

4. Limitations and future work

This work is subject to several limitations. First, although the proposed model captures the diffusion of multiple renewable energy technologies and building retrofit decisions within the residential sector, the uptake of other key transition technologies, such as electric vehicles and stationary batteries, is treated as exogenous. Incorporating endogenous adoption decisions for these technologies in future versions of the model would enable explicit representation of related incentives and policy instruments, thereby enabling a more comprehensive assessment of residential sector policy strategies.

Second, the present analysis does not systematically isolate the effects of specific policy combinations. Scenarios are generated through random sampling of policy levels and uncertain techno-economic parameters, and the clustering is performed on the resulting outputs. The identified clusters therefore reflect the joint effect of policy settings, uncertain inputs, and their interactions. For this reason, the analysis can reveal which pol-

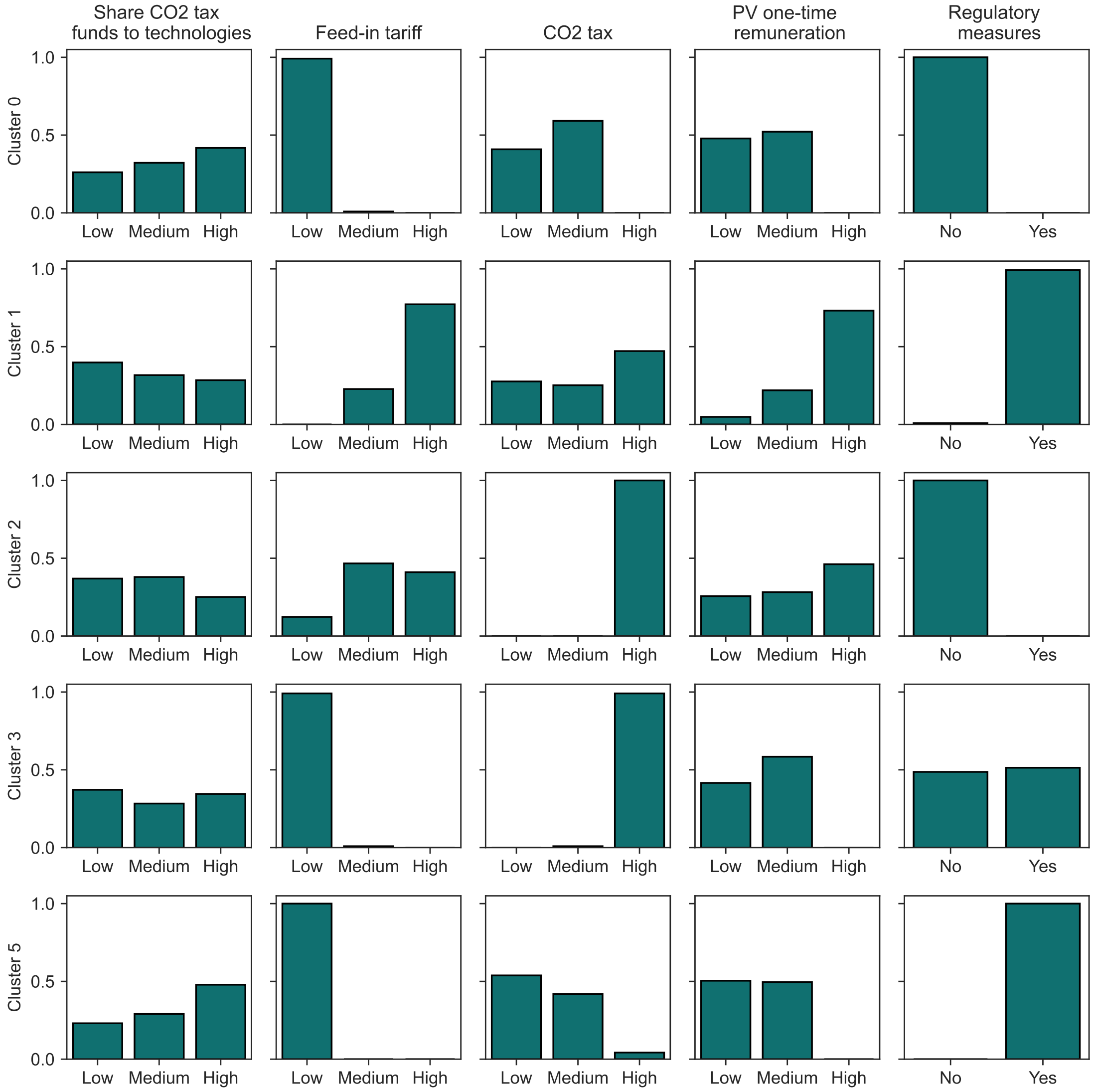

Figure 5: Relation between the five selected clusters (rows) and input policies (columns). In each subplot, the bars represent the share of scenarios in the considered cluster having a Low, Medium or High (see Section 2.6) value of the related policy input.

icy configurations are more frequently associated with certain outcome patterns, but it does not isolate the marginal contribution of each policy instrument, nor does it provide a structured exploration of all possible policy combinations. Future work could complement this approach with more explicit factorial designs, sensitivity analysis, or scenario-discovery methods to better disentangle the role of individual policies and their interactions.

In the exploratory analysis presented here, at this stage only uncertainties related to the economic and technical parameters of technologies are considered. Future research could extend the analysis to include structural model uncertainties, additional uncertain parameters, and potential changes in these parameters over the simulation period.

The conclusions drawn from the current analysis are based on the average performance of the selected clusters with respect to the indicators considered. Future work could also examine the variance within clusters. This would make it possible not only to identify policies or policy mixes that increase the probability of achieving a desirable expected outcome, but also to determine which policy configurations are more robust to uncertainty. Such an extension is particularly relevant for evidence-based policymaking, as decision-makers are often more concerned with avoiding undesirable outcomes than with maximizing a specific performance indicator.

In addition, the two inequality indicators are computed on aggregated residential segments defined by canton and building type. They therefore capture the distribution of net policy incidence across segments, but do not represent the full heterogeneity that may exist at household level. Extending the framework toward a finer representation of socio-economic heterogeneity would strengthen the assessment of distributional effects.

Finally, the proposed modeling framework could be further exploited to conduct policy optimization aimed at achieving specific target outcomes. This would involve using the developed system dynamics model as a black box and varying policy instruments over the simulation horizon, thereby explicitly accounting for the temporal dimension of policy interventions and their dynamic effects on the transition.

5. Conclusions

This paper introduced a hybrid system dynamics model to analyze alternative policy mixes for the decarbonization of the Swiss residential sector. The model integrates discrete-choice adoption of PV, heating systems, and retrofit decisions across 8,580 building archetypes with endogenous feedbacks linking electricity pricing, policy financing, and technology diffusion. The exploratory scenario analysis shows that the residential energy transition is characterized by substantial variability in outcomes and by trade-offs among policy objectives. Across the simulated scenarios, cumulative emissions, installed PV capacity, final specific heating demand, and inequality indicators span wide ranges, indicating that policy design strongly shapes residential sector outcomes. Importantly, no single policy mix simultaneously performs best across all considered dimensions. Clustering results identify distinct recurring outcome patterns, each associated with specific combinations of regulatory measures and incentive schemes.

Regulatory measures emerge as a key driver of emission reductions, particularly through their impact on heating technology choices. Higher CO_2 tax levels, in turn, are more strongly associated with lower emissions and lower final heating demand than changes in the internal allocation of subsidy revenues. However, the interaction between regulatory measures and building renovation decisions may also produce indirect effects on final energy consumption, highlighting the importance of unexpected feedbacks.

Financial incentives for PV effectively stimulate installed capacity, but they also increase the risk of distributional imbalances through the electricity levy mechanism. This result underlines the need to carefully design funding structures for renewable support schemes, especially when incentives are financed through charges borne disproportionately by non-adopters.

The CO_2 tax plays a central role in shaping both environmental and efficiency outcomes. Higher tax levels simultaneously enhance the economic attractiveness of renewable heating technologies and building retrofits, reduce cumulative emissions, and lower final specific heating demand. At the same time, the distributional implications of the CO_2 tax differ from those of the electricity levy, as tax revenues are primarily paid by fossil fuel users who are also eligible for related incentives. This distinction illustrates how the institutional design of policy financing mechanisms influences equity outcomes.

Overall, the results highlight that policy mixes, rather than individual instruments, determine the direction and quality of the transition. The proposed modeling approach provides a structured way to identify combinations of measures associated with desirable outcomes, while making explicit the trade-offs between decarbonization, energy efficiency, technology deployment, and distributional justice.

Beyond the specific findings for Switzerland, this work contributes methodologically by demonstrating how micro-level adoption behavior and macro-level system dynamics can be integrated within a coherent exploratory modeling framework. Such an approach is particularly valuable for supporting evidence-based policymaking under deep uncertainty, where the objective is not only to maximize expected performance but also to understand the robustness, trade-offs, and distributional consequences of alternative strategies.

Acknowledgements

This research was funded by the Swiss Federal Office of Energy as part of the SWEET consortium SURE and by the Swiss National Science Foundation (SNSF) 10DU–224166 in the context of the Grid-Aware Decarbonization of electricity-driven Neighbourhoods (GARDEN) project.

Author contribution statement

Matteo Palucci: Conceptualization, Data Curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - Original Draft. **Jalomi Maayan Tardif:** Conceptualization, Data Curation, Funding acquisition, Project administration, Resources, Supervision, Writing - Review & Editing. **Vasco Medici:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing - Review & Editing.

Appendix A. Calibration

To ensure that the developed model is capable of capturing the real-world behavior of the studied system, it was calibrated using historical data. In particular, the adoption and diffusion data used for calibration are the following:

- PV adoption [31]: Data were collected on the historical adoption of PV panels in the residential sector at the building archetype level. Specifically, data from 2011 to 2024 on adoption stratified by canton, building type, and energy efficiency category were used.
- Heating technologies [30]: Data were collected on the historical adoption of all the heating technologies considered in the model from 2011 to 2024. In addition, data on heat pump adoption were collected and used for calibration, stratified by canton, building type, and energy efficiency category.
- Retrofit decisions [42]: Historical data on building retrofits were collected for the period between 2011 and 2024, stratified by building type.

Moreover, historical data for several additional inputs were collected for the period between 2011 and 2024, including electricity prices, incentives across all sectors, regulatory measures, and historical technology costs. Several coefficients influencing the attributes that determine the perceived utility of a given technology were iteratively adjusted during the calibration process. For more detailed information, see [23, 25].

Appendix B. Uncertain input parameters

As explained in Section 2.6, several uncertain input parameters related to key technologies involved in the model are varied in the exploratory analysis. Tables B.1 and B.2 report these inputs as well as the ranges of uncertainty considered.

Parameter	Change with respect to baseline
Specific cost [CHF/kW]	±30%
Performance [kWh/kW]	±10%
Lifetime [years]	±10%

Table B.1: Variation of uncertain parameters with respect to baseline values in the exploratory analysis on input parameters for PV.

Parameter	Change with respect to baseline
Specific cost [CHF/kW]	±30%
Efficiency [-]	±10%
Lifetime [years]	±10%

Table B.2: Variation of uncertain parameters with respect to baseline values in the exploratory analysis on input parameters for heating technologies.

Appendix C. Clustering of results

As briefly introduced in Section 2.6, the simulation outputs were clustered using the K-means algorithm to identify groups of scenarios with similar system outcomes. K-means is an unsupervised machine learning method that partitions a dataset into K clusters by minimizing the within-cluster variance. The algorithm iteratively assigns each observation to the cluster whose centroid (mean vector) is closest in terms of Euclidean distance and then updates the centroid positions based on the observations assigned to each cluster. This process continues until cluster assignments stabilize. The resulting clusters represent groups of scenarios with similar output profiles across the considered model variables. Prior to clustering, the output variables were standardized using a z-score normalization. Specifically, each variable was transformed by subtracting its mean and dividing by its standard deviation. This transformation ensures that all variables contribute equally to the clustering process.

To determine an appropriate number of clusters, the silhouette score was computed for values of K ranging from 2 to 39, as shown in Figure C.6. The silhouette score measures how similar an observation is to its own cluster compared to other clusters, providing an indication of the separation and cohesion of the clusters. Higher silhouette scores indicate better-defined clusters. The maximum silhouette score was obtained for k = 17. However, the silhouette curve exhibited an earlier plateau around k = 10, indicating that increasing the number of clusters beyond this point yields only marginal improvements in clustering quality. For the purposes of scenario interpretation and visualization, a solution with k = 10 clusters was selected. While a larger number of clusters slightly improves the silhouette score, it also increases the complexity of the results and reduces interpretability. Selecting ten clusters provides a balance between statistical performance and analytical clarity, allowing the clustered scenarios to be interpreted as a manageable set of representative system outcome archetypes.

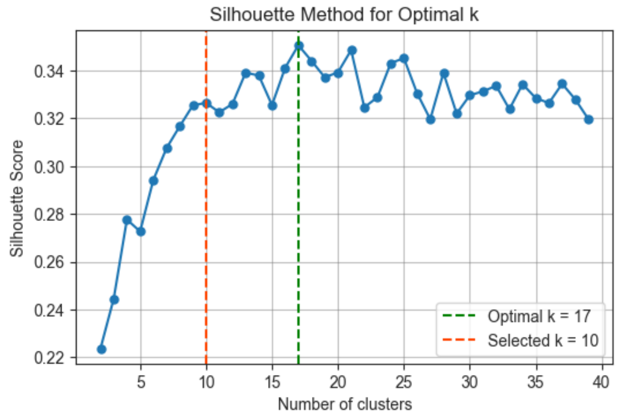

Figure C.6: Silhouette score varying the number of clusters considered between 2 and 39.

Subsequently, to enable an in-depth analysis, five clusters of particular interest were selected. The selection aimed to maximize differentiation among clusters and ensure broad coverage of the output space. To this end, the geometric distance between cluster centroids was computed in the five-dimensional output space, and the five clusters that maximized their mutual distance from the remaining clusters were chosen for further investigation.

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