Embedding local energy systems in national models: a decomposition-based coupling of multi-scale energy system

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Abstract:

Widespread electrification of energy services combined with the deployment of renewable technologies close to end users is reshaping energy systems. Buildings and districts are no longer passive consumers but active prosumers, exhibiting bidirectional electricity flows and flexibility across multiple temporal and spatial scales. Capturing these dynamics is essential to design reliable decarbonization pathways.

A rich ecosystem of decision-support tools already exists to investigate decentralization. Top–down models are well suited to national or regional energy systems, ensuring capacity adequacy, resource balances and long-term cost optimality. In parallel, bottom–up tools provide detailed optimization of building and district energy systems, including technology choices, hourly operation and local grid constraints. Despite many recent scientific works investigate the intermediate levels, most current workflows remain static: results from one model are passed to another one, with limited feedback and no coherent joint optimization.

This work addresses that gap by complementing top–down adequacy with bottom–up feasibility in a single, dynamically coupled framework. We develop an interface between two models, EnergyScope and REHO, based on a nested Dantzig-Wolfe decomposition approach. At the upper level, EnergyScope determines national-scale energy mixes, central generation capacities and high-level constraints. At the lower level, REHO represents detailed typical buildings and districts, optimizing local technology deployment and prosuming profiles subject to distribution-level constraints. Information is exchanged iteratively: the upper level provides boundary conditions and price signals, while the lower level proposes local system configurations to be integrated into the national system optimization. The modelling framework supports a coherent evaluation of the design and operation of both centralized and decentralized capacities. The methodology is validated for Switzerland, using the national building stock and existing energy infrastructures as a case study. The results show fast and optimal convergence, aligning decarbonization pathways at the local level with national objectives.

Keywords:

Decision support; Dantzig-Wolfe decomposition; decentralized energy systems; energy policy.

1. Introduction

The ongoing energy transition is characterized by a profound transformation of the way energy is harvested, distributed and consumed. Decarbonization strategies increasingly rely on two major structural trends: the electrification of end-uses and the deployment of distributed renewable energy technologies. Electrification is rapidly expanding in sectors such as space heating, through the adoption of heat pumps, and mobility, through the diffusion of electric vehicles. At the same time, photovoltaic systems, batteries and local energy management technologies are increasingly deployed close to end users.

As a result, buildings and districts are evolving from passive energy consumers into active prosumers, capable of both producing and consuming electricity while providing flexibility services to the broader energy system. These developments create bidirectional energy flows, strong temporal variability, and complex interactions between distribution networks, transmission infrastructures, and centralized generation assets.

Understanding these multi-scale interactions is critical for designing credible decarbonization pathways. However, the complexity of energy systems requires the use of decision-support models capable of capturing technical, economic and operational constraints across multiple spatial and temporal scales.

2. State of the art

A wide range of energy system modelling tools has been developed to support energy planning and policy design. These tools generally differ in their spatial resolution, technological detail, and temporal representation. Historically, two main approaches have been used to model decentralized energy systems: top-down and bottom-up formulations.

2.1. Top-down energy system models

Top-down models typically represent national or regional energy systems, focusing on energy supply, infrastructure investments and system-wide resource balances. These models are particularly well suited to analyze long-term scenarios, technology deployment pathways and the economic implications of climate policies. Examples in the literature include multi-sector systems [1], [2], national energy policy [3], investment pathways across multiple time horizons [4], and multi-regional systems [5]. One main limitation of top-down models is their coarse spatial and technical resolution which can oversimplify demand-response mechanisms, physical dynamics, and local constraints. In addition, their reliance on historical data limits their ability to capture emerging technologies and behavioral changes.

2.2 Bottom-up models for buildings and districts energy systems

Complementary approaches focus on the detailed representation of local energy systems, including buildings, districts, and distribution networks. These bottom-up models capture technology choices, operational strategies, and local constraints at a fine spatial and temporal resolution, enabling a more precise representation of local dynamics. Examples of bottom-up model applications include the design of buildings and districts energy systems [2], [6], [7], district heating systems [8], [9] or electric vehicle integration [10], [11]. Bottom-up models provide valuable insights into technology integration, local flexibility potentials, and prosumer behavior.

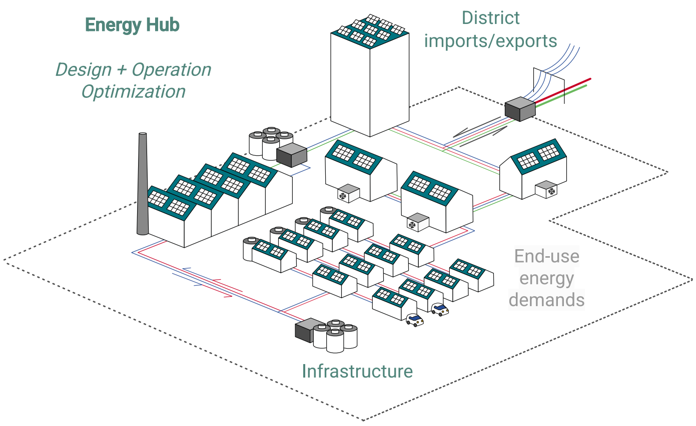

Figure. 1. Example of a bottom-up model simultaneously sizing energy technologies at the building and district scales, while optimizing the operation of local energy grids [12].

A key limitation of bottom-up models is that they usually function within narrowly defined spatial scopes and do not explicitly reflect interactions with the wider energy systems. Their weak linkage to macroeconomic indicators and dependence on fixed inputs, such as energy prices, restrict their capacity to evaluate how local solutions affect national systems and global market dynamics.

2.3 Multi-scale modelling approaches

Recent research has increasingly recognized the importance of multi-scale energy system modelling, combining different modelling approaches to capture interactions between centralized and decentralized infrastructures. Several studies have attempted to couple models operating at different scales. However, in many cases the integration remains static, meaning that outputs from one model are passed to another one in a sequential manner without iterative feedback. While this approach allows some level of consistency, it does not capture the dynamic interactions between local flexibility and system-level planning decisions.

3. Research gap

Despite significant progress in energy system modelling, an important methodological gap remains. Top-down models provide system-level adequacy and economic optimality, but they may overlook local feasibility constraints. Conversely, bottom-up models capture local technological and operational details, but they often operate independently from national planning frameworks. As a result, planning decisions derived from national models may not always be feasible at the local level, while local optimization strategies may not be aligned with system-wide economic or infrastructure constraints. Addressing this gap requires approaches capable of complementing top-down adequacy with bottom-up feasibility within a coherent modelling framework.

This paper develops a methodology based on a nested Dantzig-Wolfe decomposition to simultaneously optimize energy systems at the building, district, and national levels. The integrated modelling framework aims at enhancing the understanding of the complex energy systems spanning multiple scales, sectors, and time horizons.

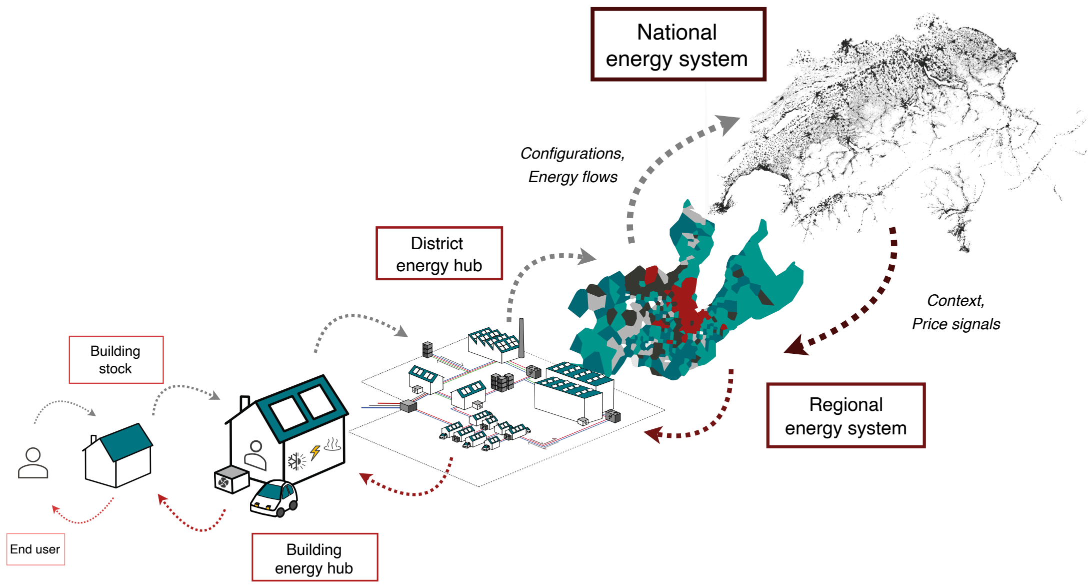

Figure. 2. *Modeling framework embedding energy (sub-)systems into larger systems.*

4. Methodology

The modeling is based on a co-optimization framework that connects two open-source tools: REHO for district-scale energy systems [12] and EnergyScope for national-scale systems [5]. Figure 4 illustrates the modeling scope of the two tools as well as their interconnection. At both neighborhood and building scales, REHO determines the investments in and operation of energy conversion and storage technologies needed to meet end-use demands for domestic hot water, domestic electricity, and space heating and cooling. To reduce operating costs, buildings can share renewable electricity with one another or feed surplus electricity into regional and national grids. The neighborhood can also import energy carriers, including electricity, natural gas, and district heat. At the national scale, EnergyScope considers energy demands in the industrial and freight sectors, as well as in neighborhoods. It determines the investments required in large-scale energy conversion technologies, seasonal storage, and energy networks expansion to meet the demands. Accounting for the techno-economic characteristics of the national system, it sends price signals to neighborhoods to adjust their consumption profiles. Finally, it determines the most suitable combination of district energy system configurations for integration into the national energy system. To limit computational effort, the building stock is typified into representative neighborhoods, following the methodology described in earlier works [6]. The joint optimization of the two models makes it possible to evaluate how investment and operational decisions interact at both local and national scales. Therefore, it allows to assess the systemic impact of decentralized technology adoption, flexibility, and prosumer profiles. Conversely, it also enables to analyze how national energy policies and climatic objectives influence the technical and economic conditions set at the boundary of neighborhoods.

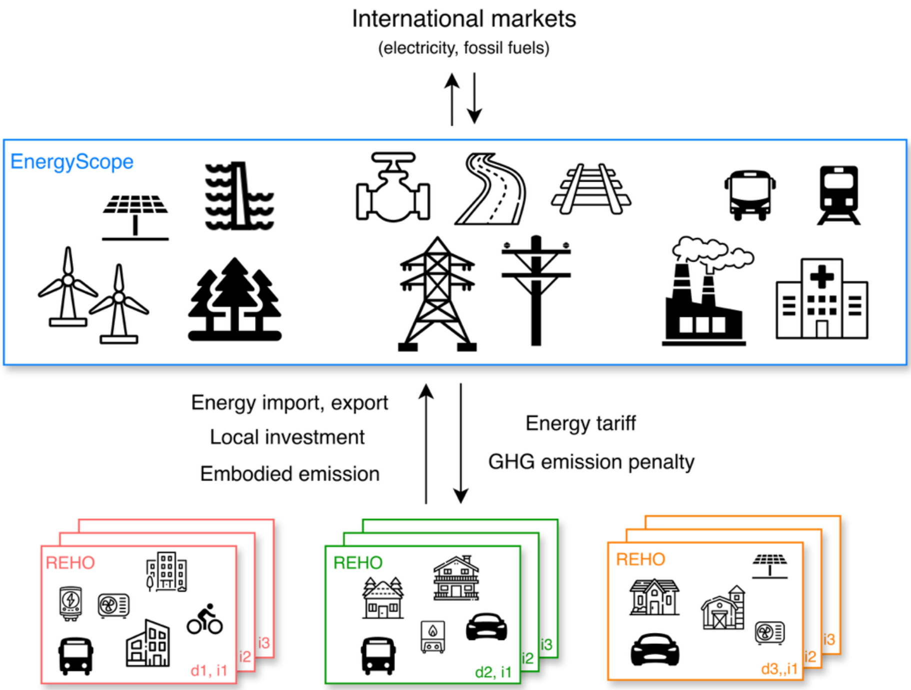

Figure. 3. *Modeling architecture representing the coupling and information exchanges between EnergyScope (upper problem) and REHO (lower problem)*

4.1 Nested Dantzig-Wolfe decomposition algorithm

In principle, each building and district problem could be solved independently if they were not connected by linking constraints, such as energy balances. This structure is well adapted to a nested Dantzig-Wolfe decomposition, in which the original problem is split into three smaller problems: a master problem **(MP)** describing the national system, a sub-problem **(SP)** modelling the buildings, and an intermediate problem **(IP)** that links the buildings to the national system and also includes investment and operation decisions regarding district-scale technologies.

As depicted in Figure 3 information between the problems is exchanged in two ways. First, the dual values of the linking constraints in the MP and IP are inserted as Lagrange multipliers in the IP and SP, respectively. This enables solving the IPs and SPs separately while indicating the techno-economic state of the upper levels. These signals aim at adjusting investment and operation in the lower levels to improve the objective function of the MP. As a response, the SPs and IPs provide new building and district configurations to be integrated in the upper levels. In the IPs and MP, a linear combination of the configurations proposed by the SPs and IPs is performed. A new variable, called λ is introduced in the IPs and MP and corresponds to the weight attributed to each SP and IP configuration.

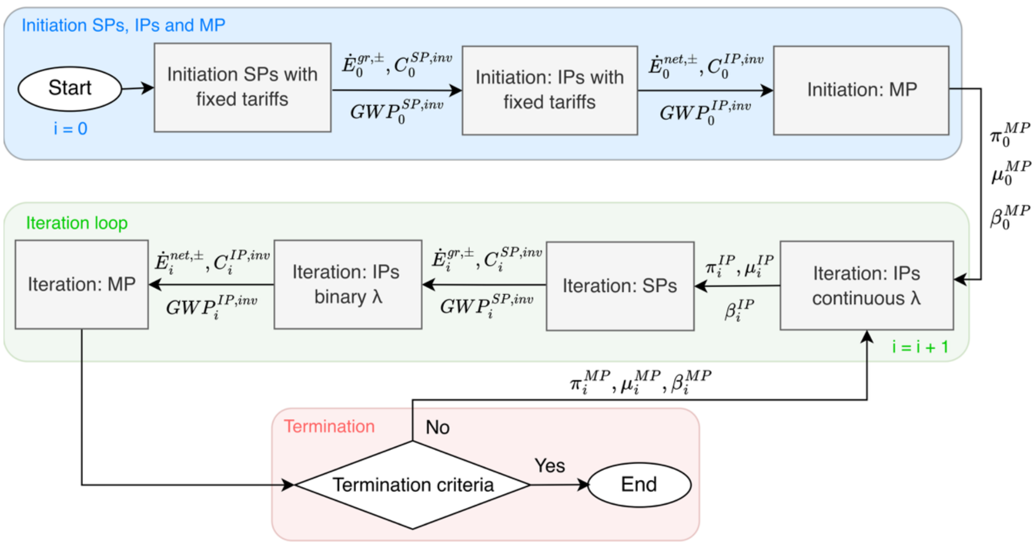

Figure. 4. *Decomposition algorithm with the initiation of the SP, IP and MP, iteration loop updating dual variables in the IP and SP, and termination.*

The algorithm, depicted in Figure 4, begins by solving each SP and subsequently each IP under the assumption of fixed energy tariffs. The resulting initial set of IP configurations is then embedded into the MP. This integration produces the first set of dual variables, which are then employed to iteratively adjust and improve the initially proposed SPs and IPs configurations. The initial assumption regarding energy tariffs is important, as it dictates the extent of PV adoption in neighborhoods and, in turn, exerts a strong influence on the energy mix of the national energy system in the early iterations.

Within the iterative loop, the dual variables play a central role, as they are responsible for guiding the convergence of the entire system. For instance, the dual value associated to the energy balance, being a linking constraint, captures the marginal cost of energy carriers. Consequently, using this value as an energy tariff in district and building energy systems allows these systems to adjust their operational choices and investment strategies in response to both the share of renewable energy in the national energy mix and the level of congestion in energy networks.

The objective functions of the IPs and SPs are represented in terms of reduced costs. A negative reduced cost implies that selecting the new configurations could improve the objective values of the MP and the IPs. Therefore, for the solution to be considered optimal, all IPs must exhibit non-negative reduced costs, indicating that no additional improvement of the MP is achievable.

4.2 Problems Formulations

In the following, decision variables are set in bold format to help the understanding of parameters being exchanged between the MP, IP and SP. The objective function of the MP is the total cost, Eq. (1), which includes both operating and investment expenses. Operating costs C^{op}, Eq. (2), include expenses associated with the harvesting of domestic resources or their purchase on international markets. Investment costs C^{inv} include the annualized expenses for large-scale energy technologies as well as the investment performed in neighborhoods $C^{IP,inv}$. The installed capacity of energy technologies is denoted by f, while f^{ext} represents their capacity already in place, such as the existing capacity of electricity grids. The decision variable λ^{MP}describes the selection of IP system configurations $i \in I$ for each district $d \in D$ and is subject to convexity constraints, Eq. (6). Analogous to the total cost calculation, the global warming potential GWP, Eq. (4), account for both embodied emissions in energy technologies at the national and neighborhood levels, and the emissions arising from their operation. Equation 5 describes the energy balance. End-use demands at the national scale ($\dot{E}^{eud}$) and in neighborhoods ($\dot{E}^{net,\pm}$) are met by the power delivered from energy conversion units ($\dot{E}$) and by energy storage units ($\dot{E}^{sto,\pm}$). Power losses $\dot{E}^{loss}$ are accounted for in each energy layer. The main linking constraints of the MP are the convexity constraints, Eq. (6), energy balances, Eq. (5), and emission cap, Eq. (4), which are respectively associated with the dual variables μ^{MP}, π^{MP} and β^{MP}. Each of these values reflects how total costs change when the corresponding constraint is relaxed. The dual values are then embedded into the IP objective function, as described in the following.

$$\text{Min } \boldsymbol{C^{op}} + \boldsymbol{C^{inv}} \tag{1}$$

$$\boldsymbol{C^{op}} = \sum_{l,t \in R,T} c_{l,t}^{op} * \boldsymbol{\dot{E}_{l,t}} * d_t \tag{2}$$

$$\boldsymbol{C^{inv}} = \frac{i(1+i)^n}{(1+i)^n - 1} * \sum_{u \in U} c_u^{inv} * (\boldsymbol{f_u} - f_u^{ext}) + \sum_{i,d \in I,D} C_{i,d}^{IP,inv} * \boldsymbol{\lambda_{i,d}^{MP}} \tag{3}$$

$$\boldsymbol{GW}P^{tot} = \sum_{u,t \in U,T} g_{u,t}^{op} * \boldsymbol{\dot{E}_{r,t}} * d_t + \sum_{u \in U} \frac{1}{l_u} * g_u^{inv} * (\boldsymbol{f_u} - f_u^{ext}) + \sum_{i,d \in I,D} GWP_{i,d}^{IP,inv} * \boldsymbol{\lambda_{i,d}^{MP}} \leq \varepsilon^{gwp} \quad \sim[\boldsymbol{\beta^{MP}}] \tag{4}$$

$$\dot{E}_{l,t}^{eud} + \sum_{i,d \in I,D} (\dot{E}_{i,d,l,t}^{net,+} - \dot{E}_{i,d,l,t}^{net,-}) * \boldsymbol{\lambda_{i,d}^{MP}} = \boldsymbol{\dot{E}_{l,t}} - \boldsymbol{\dot{E}_{l,t}^{loss}} + \sum_{s \in S} (\boldsymbol{\dot{E}_{s,l,t}^{sto,+}} - \boldsymbol{\dot{E}_{s,l,t}^{sto,-}}) \quad \sim[\boldsymbol{\pi_{l,t}^{MP}}] \tag{5}$$

$$\sum_{i \in I} \boldsymbol{\lambda_{i,d}^{MP}} = 1, \qquad 0 \leq \boldsymbol{\lambda_{i,d}^{MP}} \leq 1, \qquad \sim[\boldsymbol{\mu_d^{MP}}] \qquad\qquad \forall i,d,l,t \ \in I,D,L,T \tag{6}$$

The IP models district energy systems and integrates building energy systems into low-voltage grids, enhancing local self-consumption. Moreover, it links local energy demands with national energy grids, coordinating district operations with price signals from the MP to alleviate possible grid congestion. Finally, it shapes the design of building energy systems by transmitting price signals from the district system. The IP model is formulated in a similar way to the MP. The objective function corresponds to the reduced total cost of the district, which encompasses operating costs $C^{IP,op}$ of purchasing or selling energy $\dot{E}^{net,\pm}$ to the national networks. The marginal cost of energy carriers π^{MP} is used as energy tariffs. Investment cost includes expenses in buildings, denoted as $C^{SP,inv}$, as well as in district-scale energy technologies. The weights λ^{IP} assigned to each SP configuration are subject to the convexity constraint, Eq. (12). The dual values associated with the energy balance and convexity constraints of the IP are incorporated into the SPs' objective function to align building energy demand and electricity supply from PV capacities with the needs of both districts and national energy systems.

$$\text{Min } \boldsymbol{C^{IP,op}} + \boldsymbol{C^{IP,inv}} + \beta^{MP} * \boldsymbol{GW}P^{IP,inv} - \mu^{MP} \tag{7}$$

$$\boldsymbol{C^{IP,op}} = \sum_{l,t \in L,T} \pi_{l,t}^{MP} * (\boldsymbol{\dot{E}_{l,t}^{net,+}} - \boldsymbol{\dot{E}_{l,t}^{net,-}}) * d_t \tag{8}$$

$$\boldsymbol{C^{IP,inv}} = \frac{i(1+i)^n}{(1+i)^n - 1} * \sum_{u \in U} c_u^{inv} * (\boldsymbol{f_u} - f_u^{ext}) + \sum_{i,b \in I,B} C_{i,b}^{SP,inv} * \boldsymbol{\lambda_{i,b}^{IP}} \tag{9}$$

$$\boldsymbol{GWP^{IP,inv}} = \sum_{u \in U} \frac{1}{l_u} * g_u^{inv} * (\boldsymbol{f_u} - f_u^{ext}) + \sum_{i,b \in I,B} GWP_{i,b}^{SP,inv} * \boldsymbol{\lambda_{i,b}^{IP}} \tag{10}$$

$$\boldsymbol{\dot{E}_{l,t}^{net,+}} - \boldsymbol{\dot{E}_{l,t}^{net,-}} = \dot{E}_{l,t}^{eud} + \sum_{i,b \in I,B} (\dot{E}_{i,b,l,t}^{gr,+} - \dot{E}_{i,b,l,t}^{gr,-}) * \boldsymbol{\lambda_{i,b}^{IP}} \quad \sim[\boldsymbol{\pi_{l,t}^{IP}}] \tag{11}$$

$$\sum_{i \in I} \boldsymbol{\lambda_{i,b}^{IP}} = 1, \qquad 0 \leq \boldsymbol{\lambda_{i,b}^{IP}} \leq 1, \qquad \sim[\boldsymbol{\mu_b^{IP}}] \qquad\qquad \forall i,b,l,t \ \in I,B,L,T \tag{12}$$

The SP corresponds to the smallest subsystem, namely the building energy system. Its mathematical formulation is largely analogous to that of the IP. Both investment and operational decisions at the building level are considered, as well as energy exchanges with the district energy grids ($\dot{E}^{gr,\pm}$).

$$\text{Min } \boldsymbol{C^{SP,op}} + \boldsymbol{C^{SP,inv}} + \beta^{MP} * \boldsymbol{GWP^{SP,inv}} - \mu^{IP} \tag{13}$$

$$\boldsymbol{C^{SP,op}} = \sum_{l,t \in L,T} \pi_{l,t}^{IP} * (\boldsymbol{\dot{E}_{l,t}^{gr,+}} - \boldsymbol{\dot{E}_{l,t}^{gr,-}}) * d_t \tag{14}$$

$$C^{SP,inv} = \frac{i(1+i)^n}{(1+i)^n - 1} * \sum_{u \in U} c_u^{inv} * (\boldsymbol{f_u} - f_u^{ext}) \tag{15}$$

$$GWP^{SP,inv} = \sum_{u \in U} \frac{1}{l_u} * g_u^{inv} * (\boldsymbol{f_u} - f_u^{ext}) \tag{16}$$

$$\dot{\boldsymbol{E}}_{l,t}^{gr,+} - \dot{\boldsymbol{E}}_{l,t}^{gr,-} = \dot{E}_{l,t}^{eud} + \sum_{u \in U} (\dot{\boldsymbol{E}}_{l,u,t}^{-} - \dot{\boldsymbol{E}}_{l,u,t}^{+}) \tag{17}$$

5. Case Study: Switzerland

This case study builds on the targets established by Switzerland's long-term energy transition plan for 2050 [13]. On the building side, the complete elimination of carbon emissions is pursued by electrifying heating services. The growing demand for electricity — a direct consequence of shifting various energy services away from conventional fuels — is anticipated to be satisfied through solar photovoltaic installations and wind turbines, with these two sources together expected to contribute just over half of the annual electricity generated in the country.

Energy technologies at the building and district scales include heat pumps, electric heaters, natural gas boilers, PV panels, district heating networks, water tanks, batteries, air conditioners and buildings renovation. More information on investment cost and emobodied emissions are available in the REHO documentation [12]. At the national level, end-use demands include industrial heat and electricity requirements, along with specific energy demands for services [13]. A large list of energy technologies is modeled, including, among others, hydroelectric dams, thermal power plants, wind turbines, alpine PV, cogeneration, and synthetic gaz production and storage systems. Additional details on input parameters can be found in the online documentation of EnergyScope [14]

Twelve typical districts are used to represent urban, geographic and socio-economic characteristics of the residential sector. The k-medoids algorithm is employed, and the clustering is based on features such as the density of LV grids, the yearly mean outdoor temperature, the building form factor—defined as the ratio of roof area to indoor area—and the median household income, as detailed in the following thesis [15].

6. Results and Discussion

Figure 5 presents the convergence behavior of the decomposition algorithm. For each iteration, the figure reports operating and investment costs by sector, along with the national electricity mix and the level of GWP emissions that must be compensated via carbon capture and sequestration. In the first iteration, the high electricity tariffs used for the initialisation leads to a PV capacity that is about twice the optimal level. This leads to substantial grid reinforcement costs, being 40% more important than the optimal value at iteration 10. The PV oversizing is largely corrected after two iterations. In the subsequent iterations, a trade-off emerges between investments in renovation, heating technologies and PV panels, which further reduces total costs.

Figure 6 further illustrates how electricity price signals sent by the MP influence PV investment in the SPs. The figure reports electricity supply, storage, and exports for each month, along with the marginal cost of electricity π^{MP}, which is used as energy tariff in the IPs. The marginal cost of electricity clearly exhibits a seasonal pattern associated with PV electricity generation. During the summer months, the marginal cost of electricity is close to zero, which reduces the attractiveness of feeding electricity into the grid. In contrast, winter months feature marginal costs up to 0.5 CHF/kWh$_{el}$, driven by elevated electricity demand and limited supply. Under these conditions, self-consuming electricity from PV capacities within low-voltage grids becomes highly cost-effective, as it reduces grid imports during periods of peak prices. Consequently, using the marginal cost of electricity as both retail and feed-in tariffs in the IP, and subsequently in the SP, triggers PV investments that are appropriately aligned with the state of energy grids in each month.

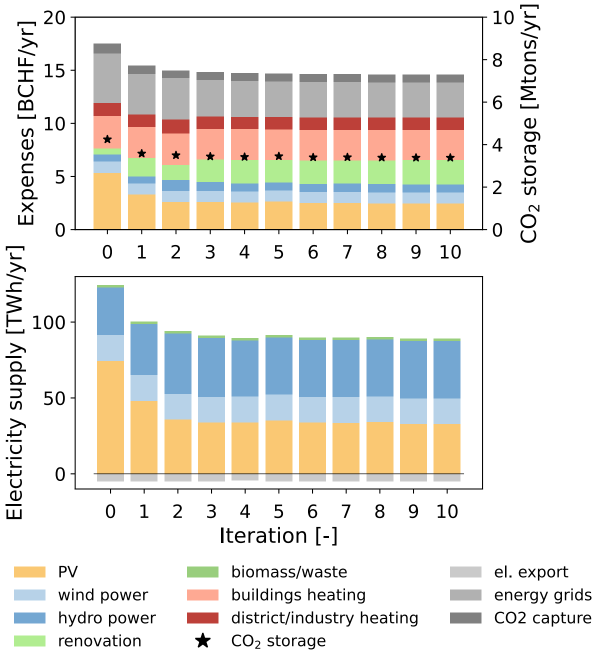

***Figure. 5.** Convergence behavior, with operating and investment costs by sector, along with national electricity mix and CO_2 emissions that need to be compensated.*

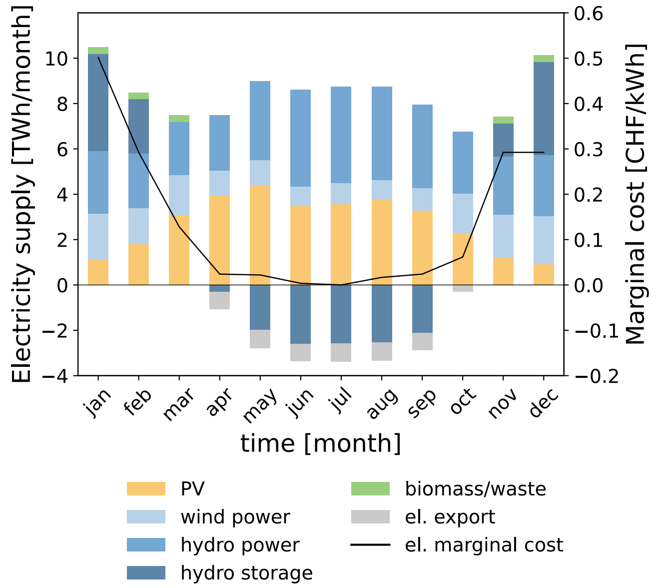

***Figure. 6.** Electricity supply, storage, and exports reported for each month of the year and each technology, along with the marginal cost of electricity (used as dynamic tariff in the subsystems).*

Finally, Figure 7 aims at illustrating the role of the dual variable β^{MP} at aligning an objective of net zero CO_2 emissions at the national level with investment decisions in buildings. The dual variable β^{MP} is associated with the CO_2 emission reduction target, Eq. (4), and can be interpreted as a carbon tax for embodied emissions in energy technologies purchased in districts and buildings. Figures 7 show that incorporating the marginal cost of CO_2 emissions into the IPs and SPs results to only a modest decrease in total costs by 0.9%. However, the optimal configuration for decentralised energy system changes substantially, as the solution relies more heavily on buildings renovation (+23.3%) to reduce space heating demand and, consequently, to mitigate embodied emissions associated with investments in PV capacity (-7.7%) and hydropower dams (-10.5%). The finding outlines the potential of the methodology proposed at translating political objectives at the national level into concrete implementations at the local levels.

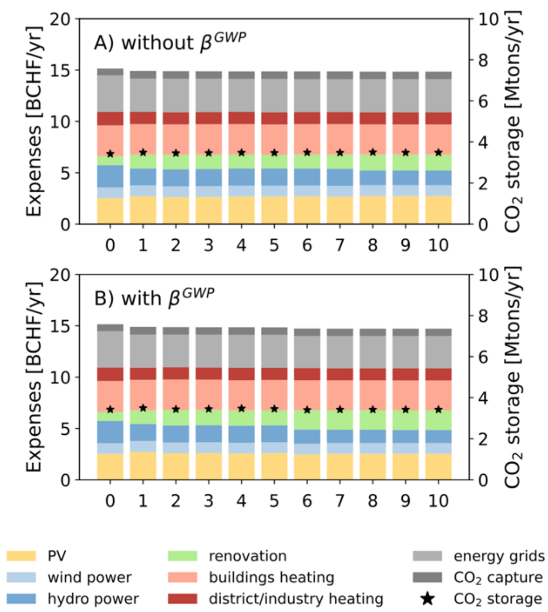

Figure 7: Total energy system cost without and with integration of the dual variable β^{MP} in the decomposition algorithm.

7. Conclusion

Embedding local energy systems within national energy planning allows to design strategies that are not only technically and economically sound, but also realistic at the decentralized level. By recognizing that the technical and regulatory dimensions are too often treated in isolation, the study highlights the need for integrated approaches that not only generate robust insights but also translate them into practical implementation at the local level. By coupling a bottom-up and a top-down model, the methodology introduces a novel multi-scale modeling framework that bridges national objective with local feasibility constraints. The Swiss case study demonstrates the added value of embedding district-level dynamics into national planning, leading to a more coherent assessment of infrastructure investments and energy pathways. Future work will further develop this framework to strengthen the connection between scientific modelling and policy design, supporting informed decision-making through open and transparent tools. The development of accessible, web-based decision-support platforms represent an important step toward democratizing complex modelling results, enabling policymakers and stakeholders to better understand and evaluate decarbonization strategies.

8. Data Availability

The data used in this study was produced with the open-source optimization tools REHO [12] and EnergyScope [5]. Readers may generate similar data using the REHO python package available here (https://pypi.org/project/REHO/) and the EnergyScope Python package available here (https://pypi.org/project/energyscope/). Documentation is provided for both tools [12], [14].

9. Fundings

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