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UrbanTwin: Development of a Local Energy Strategy and Grid Infrastructure 2050

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Abstract

The Swiss Energy Strategy 2050 aims at steering the energy supply system towards a net zero-emission target by 2050 while ensuring an efficient, renewable and secure energy supply. Achieving such an objective requires a substantial increase in electricity generation through binding targets for decentralized renewable generation. In this respect, the Swiss parliament recently increased the target of photovoltaic (PV) production for 2035 from 11.5 to 35 TWh, representing a growth of 2.2 TWh per year, compared with the yearly 6 TWh produced in 2022. At the same time, the decarbonization of districts and buildings' heating/cooling, as well as private mobility will increase the electricity demand by around 12 %, according to the Swiss Energy Outlook 2050+. This implies a large deployment of distributed PV in districts' low-voltage (LV) distribution networks, as large-scale PV plants are constrained by space needs. The combination of increased end-user consumption and distributed PV requires large investments in new assets, but also in infrastructure. In particular, the characteristics of the power flows in LV-grids will change significantly, possibly leading to overloading on lines and reduced power quality.

In this work, we propose a decision-support framework for sustainable urban energy system planning considering investment costs, operation costs and accurate modelling of boundary-conditions. Our framework integrates large datasets from in-field sensors and infrastructure in a multi-objective planning tool targeting municipalities and other governmental entities.

Introduction

Switzerland is committed to a rapid reduction of greenhouse gas emissions. Following the referendum of June 18, 2023, the approval of the “Climate and Innovation Act” means that Switzerland has legislated a reduction to net-zero emissions by 2050. The long-term climate strategy lays the foundation for emissions reduction through 10 principles, based on the “Energy Perspectives 2050+” plan from 2020 [1]. Net-zero emissions include negative emissive technologies; however, the ambition is to reduce current greenhouse gas emissions by 90%. Emission reduction is thus required across all sectors and relies heavily on electrification. Sectors with large emissions, such as buildings and mobility, should transition to renewable energy, e.g. using heat pumps for heating/cooling and battery electric vehicles (BEV). Although the Swiss electricity grid is largely decarbonized today, due to the use of nuclear and hydropower generation, the significant expected demand increase along with the progressive phase-out of nuclear power generation means additional renewable energy resources need to be added. Rosser et al. [2] estimates an additional need of 9 TWh of electricity for cars and buses in 2035, and 17 TWh in 2050. The government's response has been to promote modern renewable energies such as solar PV and wind power. The large increase in demand and intermittent supply requires investment in infrastructure. In particular, the use of distributed energy resources (DERs), such as solar rooftop PV requires careful modelling of physical flows in the LV-grid as it can become congested.

The development of sustainable and resilient energy systems is a critical challenge facing urban areas worldwide, particularly as cities strive to meet ambitious climate goals and accommodate growing populations. In this context, urban digital twins have emerged as powerful tools to aid city planners and decision-makers. These models combine big data, edge-sensing and multi-step multi-objective optimization models to build a digital replica of a city’s critical infrastructure enabling real-time observability, simulation of scenarios and planning exercises for optimal asset-utilization, cost-minimization and user satisfaction. Digital twin models spanning multiple sectors allow for sector-coupling, i.e. combining sectors such as energy, water, buildings, mobility and waste in a holistic framework to allow coordinated operation and planning. They have been enabled by the large expansion of edge-sensing devices (e.g. Internet-of-Things), large databases of in-field measurements, increased computing capacities, development of complex machine learning and statistical tools and homogenization of standards and protocols for data exchange.

To increase the utilization factor, reduce the need for costly grid expansion and minimize PV curtailment, maximum LV-grid hosting capacities must be estimated. These capacities should include grid constraints and uncertainty in production and consumption to reflect the actual grid loads. Currently, real-time monitoring of LV-grids is limited, rendering their state practically unobservable. This requires accurate planning of the network design and expansion to ensure constraints are respected during operation. The relevant grid constraints are nodal voltages, lines and transformers loading. In this respect, the legislative framework for power quality in European grids is formalized in the EN 50160 standard [3]. According to EN 50160, voltage variations in LV-grids should not exceed ±10% of the nominal voltage. Under normal operation, 95% of the 10-minute average voltage in a weekly period shall lie within the 10% limit. Line loading constraints are specified by the manufacturer and typically consist of a long-term, short-term, and emergency current-carrying limit.

LV-grids are traditionally designed with a radial topology and power-flows were historically uni-directional, i.e. from the MV/LV-transformer to the loads. However, with the increasing adoption of DER, particularly rooftop solar PV, reverse power flows can occur. The transition of LV-nodes from simple consumers to prosumers means that operational constraints might occur more often. Indeed, reverse power flows might lead to voltage constraints at certain nodes, increased lines and transformers loadings and generally larger uncertainty of the actual power flows. Furthermore, the increased complexity of the LV-grid is highly problematic because of the lack of observability and controllability of DER. Additionally, DER curtailment, for example, if nodal voltage constraints exceed the permissible values of the grid-connected inverters, leads to loss of revenue for end-consumers, often without compensation. A better understanding of the integration of DER in LV-feeders is needed to optimize the hosting capacity of DER and guarantee the whole system's safe operation.

On the path to net zero in urban areas, buildings can play a pivotal role, by operating as *renewable energy hubs*, a concept introduced by Middelhauve, 2022 [4].

Renewable energy hubs (Figure 1) maximize the use of energy from renewable sources to meet their self-demand through the optimal management of renewable energy sources and operation of energy conversion and storage technologies.

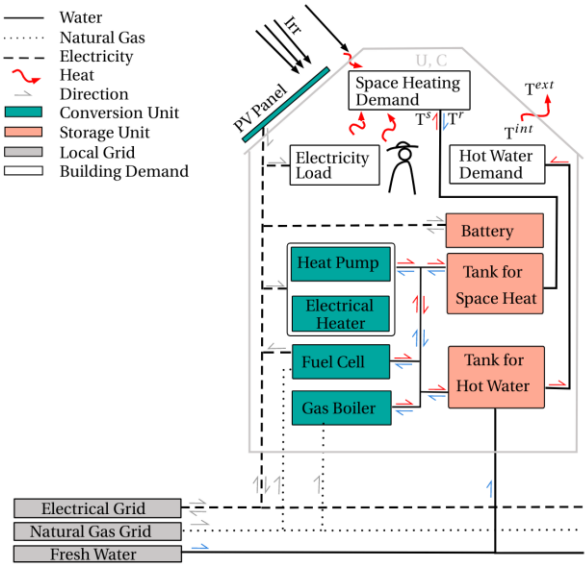


Figure 1: Representation of a renewable energy hub at the building level [4]

This work proposes a framework to integrate DERs into LV grids, aiming to maximize the use of renewable energy sources and support the transition to net-zero emission urban areas. It addresses the technical challenges and infrastructure limitations associated with this integration to ensure grid stability and reliability, support legislative and regulatory compliance, and minimize the risk of operational constraints and loss of revenue for end consumers. The framework optimizes both investment, operational and environmental costs and creates scenarios intended to support municipalities' decision-making.

2. Methodology

The integration of DERs into LV grids is a complex problem involving a wide variety of input data types and a large-scale multi-objective optimization problem, and the workflow of the framework needs to be designed carefully. The developed model jointly combines data and sub-models from different sources to allow a multi-objective optimization problem

to be solved. The different components of the model are detailed in the following sub-sections and highlighted in Figure 2. The pillar of the framework is the UrbanTwin database, which synthesizes data from different sectors to provide a unified, detailed repository of urban information. From the database, different data products are extracted, such as building information, weather data and electricity grid data and used in individual models developed within the framework. The different models communicate boundary conditions to connected models which allows them to refine constraints. The principal optimisation routine is based on the REHO tool. To find the optimal PV-hosting capacity, theoretical PV-hosting capacities based on available surfaces are generated by the REHO tool. Subsequently, the probabilistic load flow model evaluates the feasibility of the installed PV and communicates the theoretical PV hosting capacities per node back to the REHO model. This process continues iteratively until grid constraints are respected for all REHO scenarios.

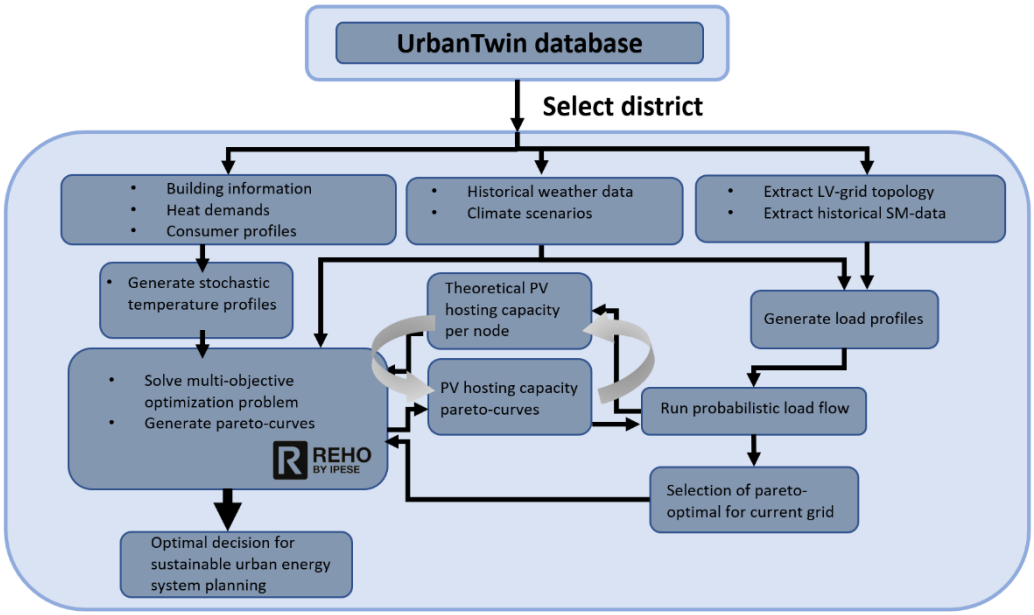


Figure 2: Overview of the model framework

2.1 REHO – multi-objective energy planning tool

REHO (Renewable Energy Hub Optimizer - https://REHO.readthedocs.io/en/main/) is an open-source decision support tool for the optimal planning of energy, considering buildings or districts as renewable energy hubs [5].

Buildings are energetically characterized by their affectation, year of construction, renovation state, and size in terms of ERA (energy reference area). Table 1 shows the characteristics of the buildings used in this study. The model considers three types of energy demands: space heating (SH), domestic hot water (DHW), and electricity for lighting and appliances. These demands are met by either importing energy from the electrical grid and natural gas grid or using available resources, such as solar energy. Load profiles for DHW and electricity of lighting and appliances are parameters of the model, which can be generated from the standardized national norm SIA 2024:2015 [6]. SH demands are modelled using a model predictive control strategy within the energy management system (EMS), ensuring the optimal operation of heat supply and storage technologies. SH demands represent the necessary heating energy to maintain the desired comfort temperature, considering both heat loss and heat gain. Heat loss in the building comes from conduction and air renewal, which are determined by the building

insulation level and the external temperature. Heat gain primarily comes from electric appliances, building occupancy, and solar irradiation.
The heating demands of a building can be satisfied by an air-water heat pump, an electrical heater or a gas boiler. Energy storage is possible using a stationary battery, domestic hot water and buffer storage or the building envelope. Photovoltaic panels can be installed on both roofs and facades, while at the same time shading from neighboring surfaces and roofs is considered, influencing the actual potential for local solar generation. This energy system is also connected to the natural gas and electricity networks, being able to import and export electricity from the grid.
The sizing of different technologies installed in a building and their operation is optimized with a mixed integer linear programming formulation considering not only the investment cost of the equipment but also the operational cost over several years. However, a detailed yearly operational analysis of the energy system in a building requires 8760 timesteps if we investigate the operation problem with an hourly resolution. This leads to a large-scale optimization problem which is intractable for current commercial mathematical solvers. Therefore, a k-medoids method is used to cluster the days into 10 typical days based on the weather data, assuming that weather conditions are periodic over the years.
Multiple-objective optimization (or Pareto optimization) was applied to capital costs (CAPEX) and operation costs (OPEX) minimizing the objective function:

$$Objective = \varepsilon \cdot CAPEX + (1 - \varepsilon)OPEX$$

Multiple energy unit configuration scenarios are obtained by varying ε in steps of 0.1 from 0 to 1.

Table 1: Parameters of the buildings in the case study

	B1	B2	B3	B4	B5
Category[1]	V/II	I	I/I/I/V/V	I	I
Year of construction/ renovation	1981-1990/ 1961-1970	1919-1945	1919-1945/ 1961-1970	<1919	1919-1945
ERA (m^2)	34261	1507	5047	651	541
Solar roof area (m^2)	9952	518	1125	317	205
Solar facade area (m^2)	20059	1126	15022	814	731
Overall heat transfer factor (kW/Km^2)	0.0017	0.0020	0.0020	0.0018	0.0020
Heat capacity (kW/Km^2)	117	120	120	120	120
Indoor temperature (°C)	20	20	20	20	20

2.2 Generation of stochastic heat-pump demand profiles

The heat-pump demand profiles are obtained by REHO, which assumes a deterministic behaviour of the variables that affect it. This results in an unrealistic trend. In this research, we suppose that the values of the external temperature and solar irradiance obtained after clustering are the ground truth, however, we model random fluctuations around these data by Stochastic Differential Equation (SDE).
This approach is motivated by the uncertain nature of temperature and solar irradiance and the propagation of the uncertainty induced by the clustering process.
We report the stochastic model used for the temperature; a similar one is used for solar irradiance.
We suppose that the normalized value of the temperature follows the SDE:

$$dT(t) = \left(\frac{dT_{ref}(t)}{dt} - \gamma\left(T(t) - T_{ref}(t)\right)\right)dt + \sqrt{2\sigma T(t)\left(1 - T(t)\right)}\, dW(t),$$

where $T_{ref}(t)$ is a reference temperature profile, in our case, to achieve differentiability, we use a trigonometric approximation of the true profile. γ, σ are two positive parameters estimated from the correlogram and the quadratic variation of the process respectively. For more details about the properties of this model, we refer, e.g., to [7].

We use the same SDE model for each typical day, however, different values of the parameter γ are inferred for each of these days. A fixed value of □ is instead estimated from the complete time-history. With this model at our disposal, we can run MC simulation to create several possible scenarios of temperature and irradiance for each typical day.

In Figure 3 we report the temperature of the first typical day (red line) and confidence intervals obtained by simulating the SDE trajectory 10000 times. These trajectories can then be used in REHO to represent a sample of the real temperature value for a given day.

[1] (I to XII) based on SIA 2024:2015 [6]

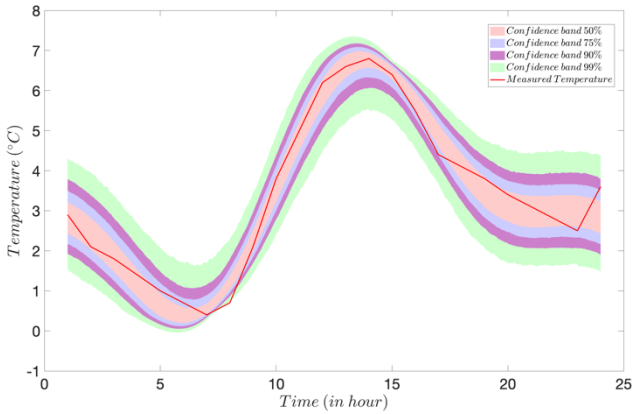


Figure 3: Measured temperature and associated confidence intervals for 10000 simulations.

2.3 Electrical distribution grid

Modelling of the electricity grid is done by combining measured values, real grid topology and associated electrical models along with scenario-based optimization. The Lausanne distribution grid consists of more than 700 MV/LV (11/0.4 kV) transformer stations. A digital version of the network has already been implemented in NEPLAN, specifying voltage levels, transformer and line parameters and topology. In the proposed framework, the user can either select an MV/LV transformer, a district or a household. Then, the associated LV-feeder specifications are extracted for the study in question. The MV/LV transformer along with the LV-feeder used in the case study is shown in Figure 4.

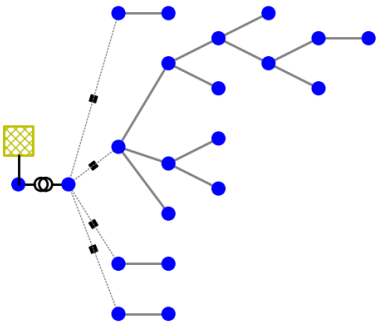


Figure 4: LV-feeder topology in the case study.

Measured values of electricity consumption per 15-minutes are obtained from Smart Meters (SMs) located at every end-consumer and aggregated at building-level to address privacy concerns. The associated loads are a mix of residential and commercial (see Table 1).

2.4 Modelling uncertainty in the LV-grid

Since both residential loads, DER-production, and heating profiles are uncertain, the resulting impact on the grid is uncertain. To assess the adequacy of the LV-feeder for different scenarios, we run stochastic power flow studies using the Monte-Carlo approach and verify probabilistically that grid constraints are respected. To this end, simulations are run hourly for a typical day in each of the 4 seasons. The uncertainties considered are listed in Table 2 and Figure 5 highlight the Monte-Carlo algorithm. In the initialization, an LV-feeder is selected along with its corresponding MV/LV transformer, the admittance matrix Y_{BUS}, base power S_N and base voltage V_N as well as the parameters of the simulation. Iterating over all the 10 REHO Pareto-curves, we solve the load flow problem for different realizations of the random variables. For every iteration of the MC-simulation, we draw a realization of the random variables for a specific REHO-pareto curve, season and hour in the day. The stopping criteria for the Monte-Carlo simulations is the Gaussian stopping rule [8] with a confidence level of p=0.95 for a tolerance of 1e-3.

Table 2: Overview of random variables in the Monte-Carlo simulations

Random variable	Probabilistic description
Slack node voltage magnitude: V_0	Truncated Gaussian
Residential electricity demand: P_{res}, Q_{res}	Gaussian kernel density estimation on SM data clustered by hour-of-day
Heat Pump electricity demand: P_{HP}, Q_{HP}	Scenario from REHO
Global Horizontal Irradiance: GHI	Gaussian kernel density estimation on historic data clustered by season and hour-of-day

2.4.1 Modeling of random variables

The nodal voltage at the slack bus (primary side of MV/LV transformer) is influenced by the state of the higher-level grid. This is taken into account by modelling it as a truncated Gaussian distribution centred at 1.02 per unit (p.u.) with a standard deviation 4e-3 p.u. and truncation at 0.97 and 1.06 p.u.

Residential load profiles are generated by clustering historical load profiles by hour of the day and assessing the cross-correlation between buildings. Nodes that have a significant cross-correlation are grouped and modelled with a multivariate kernel density estimation based on Gaussian kernels. This ensures that the correlation-structure present in historical data is reflected when scenarios are drawn for the Monte-Carlo simulations.

The REHO model generates 10 heating demand profiles per building, for every pareto-curve. The 10 profiles reflect typical days in a year. Finally, the REHO model also generates a list of installed PV-panels per building, for every Pareto-curve. This list includes the tilt angle, the orientation (azimuth) and the rated power of the PV panels. To estimate the AC-power output of the PV-panels given the GHI, we estimate the plane-of-

array irradiance using the PVLIB library [9]. Plane-of-array irradiance is converted into AC-power considering the standard panel efficiency, temperature coefficient of power and inverter losses.

```
Pseudo-code: Stochastic power flow
initialize:
    grid ← (Y_BUS, S_N, U_N)
    params ← (max_iter, season, hour_of_day)
for REHO_scenario=1:10:
    for it=1:max_iter:
        [V_0, P_res, P_HP, GHI] ← sample(REHO_scenario, season, hour_of_day)
        PV injections ← GHI_to_power(GHI, REHO_scenario, season, hour_of_day)
        Nodal residential loads ← P_res
        Nodal HP loads ← P_HP
        result[REHO_scenario,it] = solve_LF(V_0, P_c, Q_c, P_g, V_g)
        stop_condition = evaluate_stopping_condition(result, it)
        if stop_condition==True:
            it ← max_iter
return result
```

Figure 5: Stochastic power-flow algorithm using Monte-Carlo sampling.

2.5 Case study

In the case study, we showcase the results of applying the UrbanTwin framework to a neighbourhood in Lausanne. The neighborhood consists of 5 buildings and their parameters are given in Table 1. The buildings are supplied by a low-voltage feeder of the Lausanne electricity grid (see Figure 4) and in the case study, we consider the feasibility of replacing the current heating system, which is a combination of gas and fuel oil, with HPs, as well as the maximum PV hosting capacity.

3. Results

We first assess the PV hosting capacity of the grid and through the iterative process, we reduce PV capacities allocated by REHO until all Pareto curves are feasible for the grid. The stochastic temperature profiles are used by REHO to generate heat demand profiles. In this instance, we examine a scenario where all buildings install HPs to cover their heating demands. We also verify that the additional loads do not violate the constraints of the LV-feeder.

3.1 Grid constraints violation

We assess the feasibility of REHO's Pareto curves by calculating probabilistic nodal voltage deviations and line and transformer loadings in the LV-feeder. We report the results from typical summer days and typical winter days, reflecting constraints related to PV-injections and HP-loads, respectively.

3.1.1 Summer Day

In the summer, HP-loads are minimal, and the grid constraints are related to PV-injections. This typically leads to the largest *reverse* power flows in a LV-feeder. Figure 6 shows the resulting impact on nodal voltage deviations and lines and transformer loadings after the optimisation routine to select the maximum PV hosting capacity. Initially, line loadings exceeded 300% using the available surface area for installing PV panels. The iterative process of our framework reduces PV hosting capacity until grid constraints are respected for all REHO scenarios. The grid operator now has a holistic view of the grid planning exercise; on the one hand, they can accurately quantify the PV hosting capacity with the current grid, allowing to limit costly grid expansions. On the other hand, they can visually

map grid elements which are operating close to their capacity and therefore plan expansions or reinforcements accordingly.

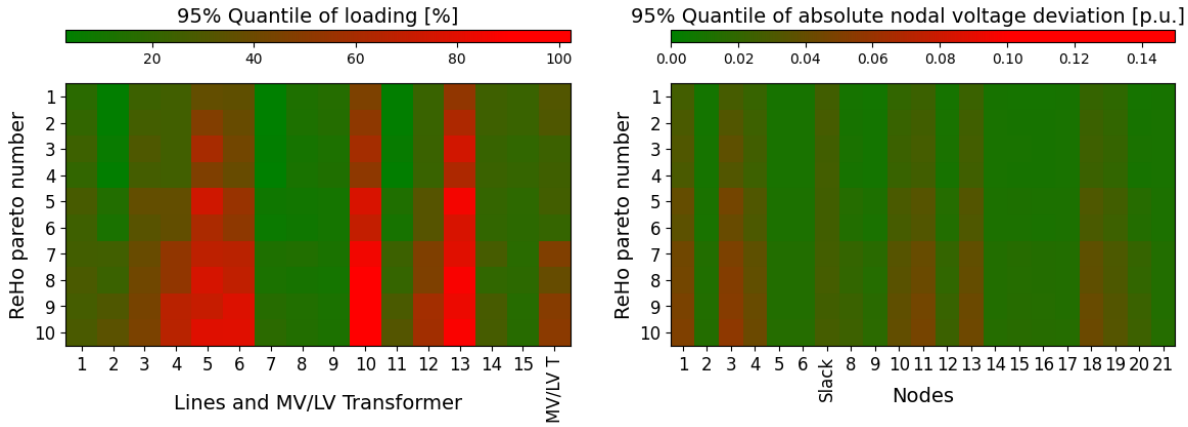


Figure 6: Grid constraint results for the REHO pareto results *after* limiting the PV boundary conditions. **Left:** 95% quantile of loading for all the lines and the MV/LV transformer. **Right:** the 95% quantile of absolute deviations from the per-unit reference voltage. We only report the worst-case values overall 24 hours of a day. As seen, there are no violations of line or transformer loadings or nodal voltages for all REHO scenarios.

3.1.2 Winter Day

In the winter, HP demand is at its highest while PV production is at its lowest. This typically leads to the highest power flows in a LV-feeder. Figure 7 shows the resulting grid loadings in a scenario where all heating demands are covered by HPs.

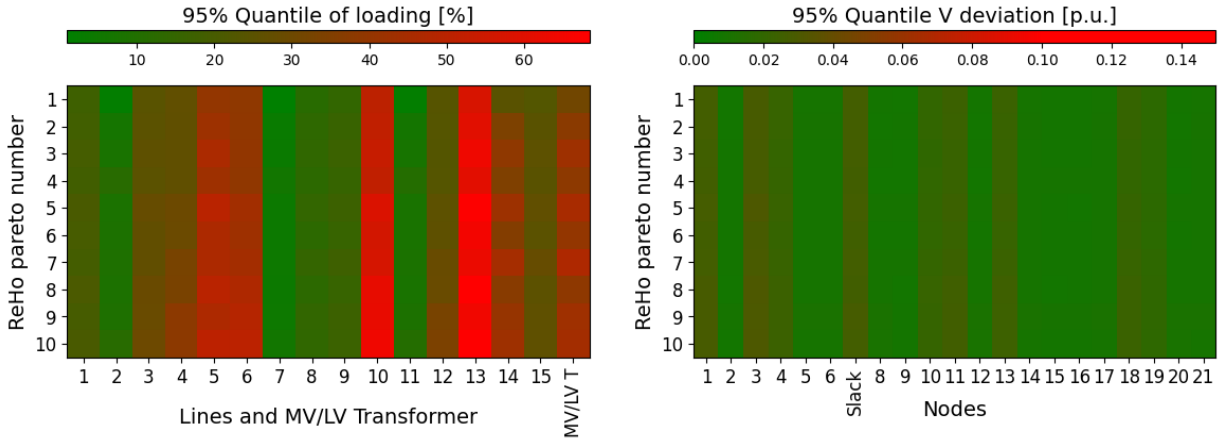
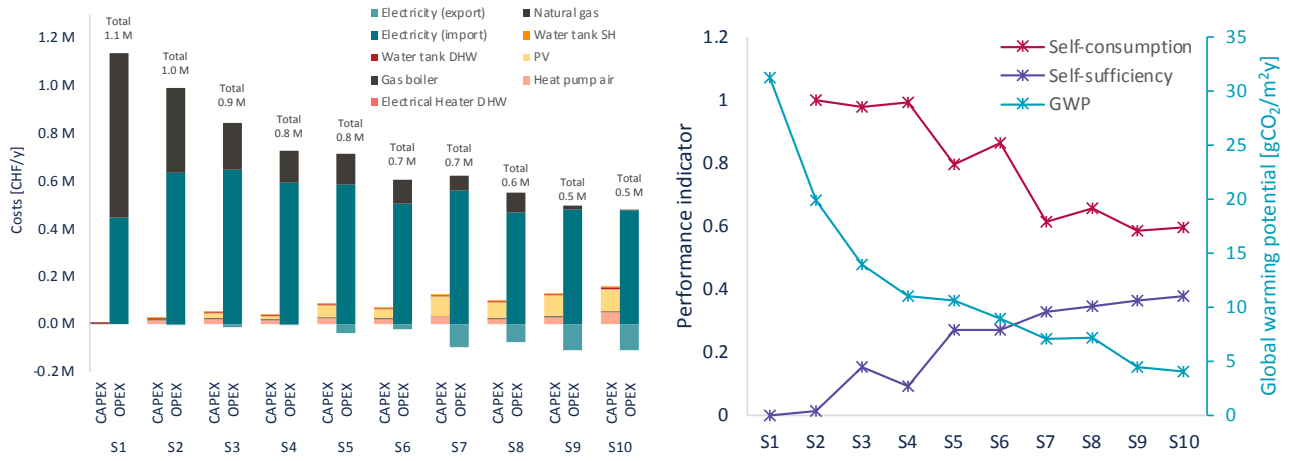


Figure 7: Grid constraint results for the REHO pareto results of a typical winter day. **Left:** 95% quantile of loading for all the lines and the MV/LV transformer. **Right:** the 95% quantile of absolute deviations from the per-unit reference voltage. We only report the worst-case values overall 24 hours of a day. We observe that grid loadings only increase mildly for all REHO-scenarios.

3.2 REHO Results

Figures 8 (a) and (b) present the results from the multi-objective optimization after applying the constraint on maximum PV hosting capacity, and their impact on some performance indicators.



(a) (b)

Figure 8: REHO results of the multi-objective optimization after the implementation of the constraint on the maximum PV hosting capacity. (a) Detail on the costs. (b) Performance indicators.

The introduction of epsilon constraints (ε), enables the decision-maker to explore a broader range of solutions and analyze the trade-offs between different energy system configurations. As greater emphasis is given to capital expenditures, the system increasingly depends on the district grid (lower levels of self-sufficiency), resulting in significantly higher operational and total costs, as well as higher environmental impacts. In contrast, the adoption of decentralized energy systems proves to be advantageous for reducing the total cost of the energy system, and the emissions of CO_2.

Conclusion

In this paper, we present a decision-support framework for sustainable urban energy system planning based on a digital twin. The framework consists of a comprehensive database, multiple individual models that share boundary conditions between them, and a central multi-objective energy infrastructure optimization tool to optimally design an energy system. The utility of the framework is showcased in a case study to optimally plan the expansion of rooftop PV in a LV-feeder and verify the adequacy of current grid infrastructure to support the build-out of HPs to cover heating needs in Lausanne, Switzerland. The combination of an accurate model of the electricity grid, considering uncertainties on production, consumption and slack nodal voltage, and the multi-objective optimization planning tool REHO gives utilities the freedom to explore different scenarios and trade-offs between CAPEX and OPEX costs. In the future, we seek to expand the model by including climate scenarios, EV-charging demand and flexible resources such as community energy storage systems.

Acknowledgement

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