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REHO: A Decision Support Tool for Renewable Energy Communities

Dorsan Lepour [1¶], **Joseph Loustau** [1], **Cédric Terrier** [1], **and François Maréchal** [1]

1 Industrial Process and Energy Systems Engineering, École Polytechnique Fédérale de Lausanne, Switzerland ¶ Corresponding author

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Summary

The transition to sustainable energy systems in the face of growing renewable energy adoption and electrification is a complex and critical challenge. The *Renewable Energy Hub Optimizer* (REHO) emerges as a powerful decision support tool designed to investigate the deployment of energy conversion and storage technologies in this evolving landscape. REHO leverages a Mixed-Integer Linear Programming (MILP) framework combined with a Dantzig-Wolfe decomposition algorithm to simultaneously address the optimal design and operation of district energy systems, catering to multi-objective considerations across economic, environmental, and efficiency criteria.

REHO is deployed as an open-source and collaborative Python library, available as a PyPI package and supported by comprehensive documentation. The documentation website includes step-by-step instructions, details about the mathematical background and model foundations, as well as a list of academic publications, conference proceedings, research projects, and other works related to REHO.

This paper introduces REHO and highlights its key features and contributions to the field of sustainable energy system planning.

Statement of need

Cities around the world are moving towards increasing the penetration of local energy harvesting and storage capacities to render their energy consumption more sustainable and less dependent on a geopolitical context. The intensification of renewables deployment is witnessed in the past decade and keeps continuing, leading to important techno-economic-social trade-offs in energy strategy. This transition blurs the boundaries between demand and supply and creates new types of stakeholders. Adopting a district-level approach for energy system planning seems thus particularly relevant, as it promotes the valorization of endogenous resources and enables economies of scale while preserving local governance (Heldeweg & Saintier, 2020). The emergence of the concept of energy communities is a clear example of this growing interest for energy planning at the neighborhood scale (Doci et al., 2014). Energy communities are expected to play a pivotal role in the ongoing energy transition by fostering decentralized, sustainable, and community-driven approaches to energy production and consumption. Through the collaborative efforts of residents, utilities, and institutions, energy communities offer a techno-economic framework to support the paradigm shift from centralized to distributed and district-level energy systems (Caramizaru & Uihlein, 2020).

Optimizing a district-level energy system is a complex and computationally intensive task due to its network structure and interdependent decision variables. Facing this problem, a common method is to fix some degrees of freedom through assumptions and scenarios based on expert knowledge (Pickering & Choudhary, 2019; Reynolds et al., 2019). Many studies in literature assume energy demand profiles (Murray et al., 2020) or predetermine the energy system configuration (Alhamwi et al., 2018; Chakrabarti et al., 2019; Kramer et al., 2017). The issue with such assumptions is the consideration of energy carriers to be delivered instead of energy end-use demands to be satisfied. By assuming a priori some investment decisions into energy capacities, the solution space is reduced, and such model does not unveil the full potential of energy communities. However, modeling subsystems as entities embedded in a larger system should reveal the interdependency of the decision-making and exploit the main benefits of energy communities to coordinate decisions both at the building- and district-level.

In the field of district energy systems design, diverse open-source decision support tools exist, but only partially meet the challenges that studying energy communities represents:

- `EnergyPlus` (Crawley et al., 2001), and its extensions such as `CESAR-P` (Orehounig et al., 2022), are simulation models, lacking an optimization feature.
- `Calliope` (Pfenninger & Pickering, 2018) and `ModelicaBuildings` (Wetter et al., 2014) do not support multi-objective optimization.
- Some tools focus on a specific energy carrier; we can mention here `Clover` (Sandwell et al., 2023) for electricity, `PyHeatDemand` (Jüstel & Strozyk, 2024) for heating, or `RHEIA` (Coppitters et al., 2022) for hydrogen. While they are certainly relevant to specific areas of study, they do not adequately grasp the holistic nature of optimizing a multi-carrier energy system.
- `OSeMOSYS` (Howells et al., 2011), `EnergyPLAN` (Lund et al., 2021) or `EnergyScope` (Limpens et al., 2019) focus on national energy systems and do not model buildings and their interactions with sufficient granularity (e.g., no heat cascade and distinction of temperature sets).
- Eventually, `CityEnergyAnalyst` (Fonseca et al., 2024) or `oemof-solph` (Krien et al., 2024) – and its extensions such as `SESMG` (Klemm et al., 2023) –, provide interesting frameworks for buildings energy systems optimization, but their district upscaling feature does not allow to explore the overarching implications of building-level decisions so that their investigations predominantly hinge on an absolute district-level perspective without distinction of the different stakeholders.

This gap has motivated the development of *Renewable Energy Hub Optimizer (REHO)*, a comprehensive decision support tool for energy system planning at the district-level, considering simultaneously diverse end-use demands, multi-energy integration, and building interactions.

Initially developed within the *Industrial Process and Energy Systems Engineering* research group (IPESE, EPFL), REHO is now made public, with a diverse target audience extending from academia and research projects to decision-makers for municipalities, energy utilities and industrial sectors.

Model foundations

The energy hub concept (Mohammadi et al., 2017) is used to model an energy community where multi-energy carriers can supply diverse end-use demands through building units and district units optimally interconnected and operated.

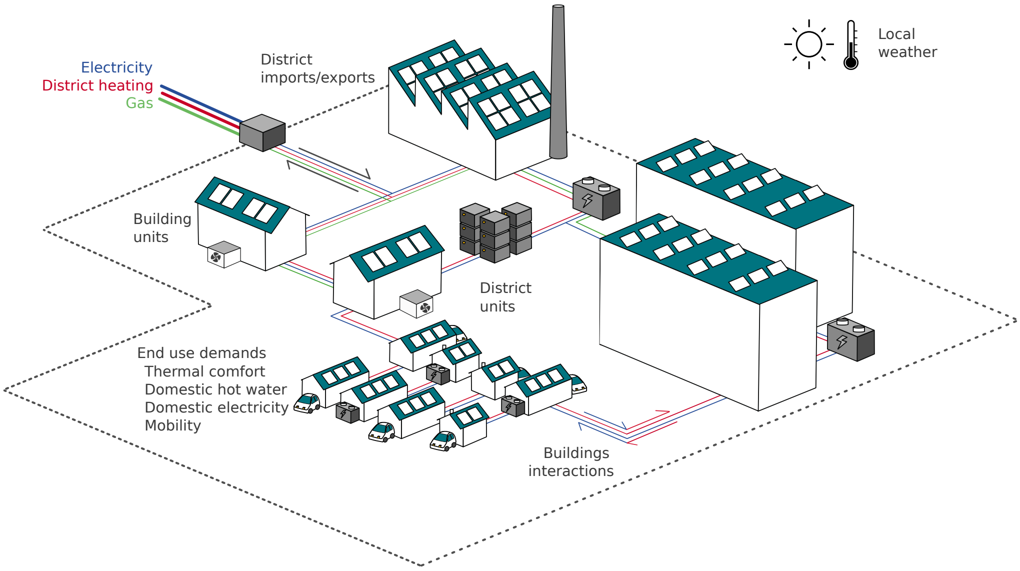

Figure 1: District energy hub model in REHO.

Figure 1 displays the input data necessary to characterize a district-level energy hub to be optimized with REHO:

- The geographic boundaries of the considered territory;
- The end-use demands, resulting from the building stock characteristics and local weather;
- The technologies available and their specifications regarding cost, life cycle, and efficiency;
- The endogenous resources;
- And the energy market prices for district imports and exports.

The optimal solution minimizing the specified objective function will then be fully characterized by the decision variables defining the energy system configuration. These decision variables are the installed capacities of the building and district units among the available technologies, their operation throughout a typical year, and the resulting energy flows (building interactions and district imports/exports).

Implementation

REHO exploits the benefits of two programming languages to explore the solution space defined by the district energy hub input data. Figure 2 illustrates the tool architecture:

- The data management structure is written in Python and used for input parameters preprocessing, and decision variables postprocessing.
- The optimization model is written in AMPL, encompassing objective functions, modeling equations, and constraints at building-level and district-level.

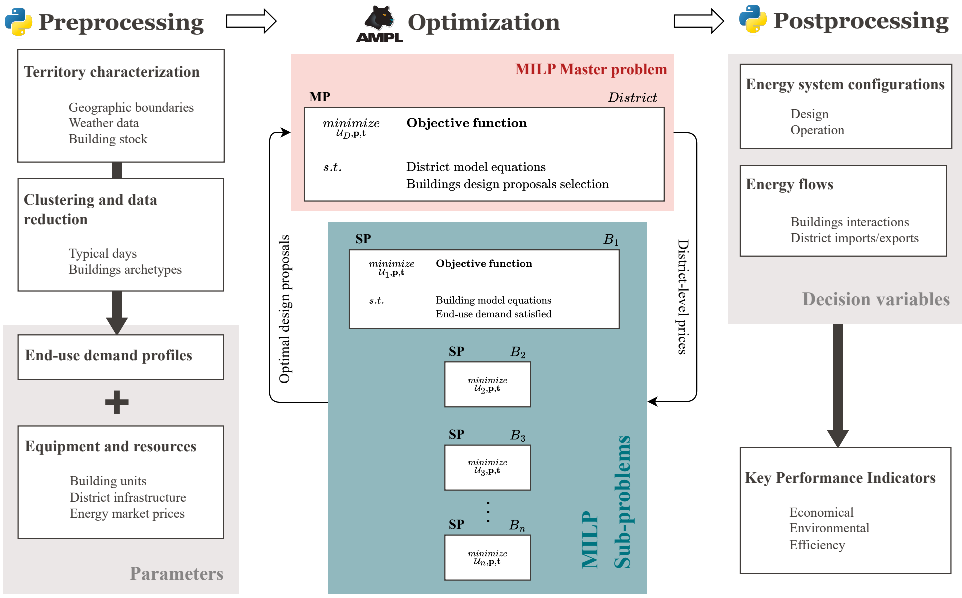

Figure 2: Diagram of REHO architecture.

Data reduction

The task of optimally designing and scheduling energy systems with a high share of renewable energies is complex and computationally demanding. REHO includes machine learning techniques to cluster yearly input data. The model operates in the conventional way with typical periods of 24 timesteps, but it can be freely adapted to a finer or coarser granularity as required.

MILP formulation with decomposition

A Dantzig-Wolfe decomposition is applied to the overall problem to define a master problem (MP) for district-level perspective and one sub-problem (SP) for each building. Linking constraints allow the problem to iteratively converge to the solution minimizing the global objective function: the MP sends district-level marginal costs to the SPs, which in turn send back building-level design proposals.

Embedded features

Multi-Service Consideration

REHO encompasses a wide range of end-use demands, including thermal comfort (heating and cooling loads), domestic hot water, domestic electricity, mobility, and information and communication technologies (ICT) energy needs.

Multi-Energy Integration

REHO incorporates various energy sources and networks, such as electricity, fossil fuels, biofuels (hydrogen, biomethane), and district heating and cooling networks. This holistic approach ensures a comprehensive representation of the energy landscape.

Multi-Scale Capabilities

REHO's flexibility spans various scales, from individual buildings to entire districts. The district-scale optimization feature capitalizes on synergies between buildings, allowing them to function as an energy community and enabling energy flows between buildings. In addition, such an approach opens the possibility of deploying district-level infrastructures.

Multi-Objective Optimization

REHO's versatility extends to multi-objective optimization, accommodating objectives related to economic (capital and operational costs), environmental (life cycle analysis and global warming potential), and efficiency criteria. Epsilon constraints provide fine-grained control, enabling decision-makers to explore trade-offs and identify Pareto fronts.

PV orientation

Given the pivotal role of photovoltaic (PV) systems in the energy transition, their optimal deployment is of paramount importance and must consider the specific characteristics of the building morphology, the local solar irradiance, and the local power grid integration. REHO integrates the deployment of solar panels on roofs and facades, with the possibility of taking into consideration the orientation of surfaces.

Electric mobility

REHO enables the integration of electric vehicles into neighborhoods, including the possibility of smart charging, unidirectional or bidirectional. The fleet of electric vehicles can thus be used to provide an energy storage service.

Grid constraints

As the electrification of diverse sectors gains momentum, the demands placed on the electricity grid are expected to further escalate. The existing electrical grid, originally designed for centralized power generation and unidirectional energy flows, now faces new demands and complexities. REHO allows for the consideration of the local grid specifications, through line and transformer capacities, as well as peak power shaving and curtailment measures.

District heating and cooling

REHO enables the deployment of district heating and cooling networks, with consideration of several heat transfer fluids and distribution temperatures. Infrastructure costs are also incorporated, based on the topology of the considered neighborhood.

Interoperability

From a technical standpoint, REHO is designed to be user-friendly, with a modular structure that allows for easy customization and extension. The interoperability of REHO boasts its capability to interface and exchange information with other tools, enabling extensive studies in the field of energy communities and for a wide range of both research and practial applications. The *Relases* section of REHO documentation keeps track of all publications and public projects related to REHO.

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