STOCHASTIC PROGRAMMING IN ENERGY COMMUNITIES: HEAT PUMP AS FLEXIBILITY

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Introduction

With rising energy demand as well as rising renewable energy generation, flexible energy storage becomes increasingly important for grid stability and energy efficiency. The concept of energy communities (ECs) is proposing a local renewable generation and consumption method, gaining popularity in the European Union [1]. Energy generation and demand forecasting provides a basis for grid flexibility calculation. The presented model uses stochastic non-linear programming to optimize the energy cost via power-to-heat sector coupling of an EC by implementing space-heating (SH) and domestic hot water (DHW) heat pump systems into simulated EC buildings.

Methodology

The simulation is realized with the mpi-sppy package in Python [2]. As a grey-box approach to a heating simulator, the thermal system is split into internal and external parameters [3]. Internal parameters define building geometry, room and wall heat capacity, heat losses, occupation, a hot water tank model and separated space and water heat pumps with electrical power, performance parameters as well as temperature bounds. External parameters include a meteorological forecast time series from the German Weather Service (DWD) for a specific set of coordinates which drive the model via ambient temperature, solar irradiance and wind speed [4]. The mpi-sppy extension allows to embed the resulting thermal dynamics into stochastic optimization as discrete energy balance equations for room and tank temperatures, along with draw events for different occupancy scenarios.

As shown in Figure 1, the EC uses an internal battery as energy storage, which can be charged through the grid as well as through local PV generation, using the meteorological forecast provided by the DWD to compute stochastic energy generation scenarios. The baseload demand of the EC must always be met and is modeled as a continuous sinewave with an additional randomizer for this example. As shown in Figure 1, the SH heat pump can operate as a space heating and cooling mechanism to keep the temperature inside the bounds, set to a minimum of 20°C and a maximum of 23°C in this example. The DHW temperature is set to a maximum of 45°C which must be provided when a draw event is triggered, relying on three usage scenarios.

The heat demand is enforced via penalty functions, which are combined with electricity cost alongside battery and optional EV penalties, to compute an objective function for the solver.

$$C_{hp}(t) = \sqrt{e^{\Delta T_{min}(t)+1} + e^{\Delta T_{max}(t)+1}} \qquad (1)$$

The objective function includes all penalty costs into a minimizer. The weight of the penalties changes the cost functions behavior, so adjusting the magnitude of the penalty cost directly influences the non-optimal regions of the function.

$$C(t) \;=\; \arg\min \textstyle\sum_{t\in T}\left(c_{el}(t)^2 + c_{soc}(t) + c_{car}(t) + c_{sh}(t) + c_{dhw}(t)\right) \qquad (2)$$

In scenarios with SH and DHW enabled, heating demand competes with battery charging while the solver prioritizes avoiding temperature penalties over maximizing battery arbitrage. Temperatures are kept close to their comfort midpoints to preserve electrical flexibility for meeting demand constraints. The solver is powering the heating and cooling mechanisms of the SH system simultaneously, which is cost-optimal, given the negative energy prices during that period. The results demonstrate that integrating a heat pump based heating model into the optimizer can provide additional flexibility for cost effectiveness and can support the use of buildings as energy sinks, relying on the batteries state of charge and the energy price at each timestep. The potential of heat pumps for energy storage and the usage of model-predictive control is evaluated through the temporal shift of electrical load under the

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given constraints. Analysing the changes in total energy cost, battery utilisation, room and tank temperatures relative to a reference case without flexible operation can provide a more accurate assessment of the stochastic optimizer's efficiency. The accuracy of the optimization problem may be increased by implementing predicted energy prices for the given time interval instead of approximating an energy price curve. The use of a standardised baseload, including the fitting energy consumption data, may increase the solvers accuracy.

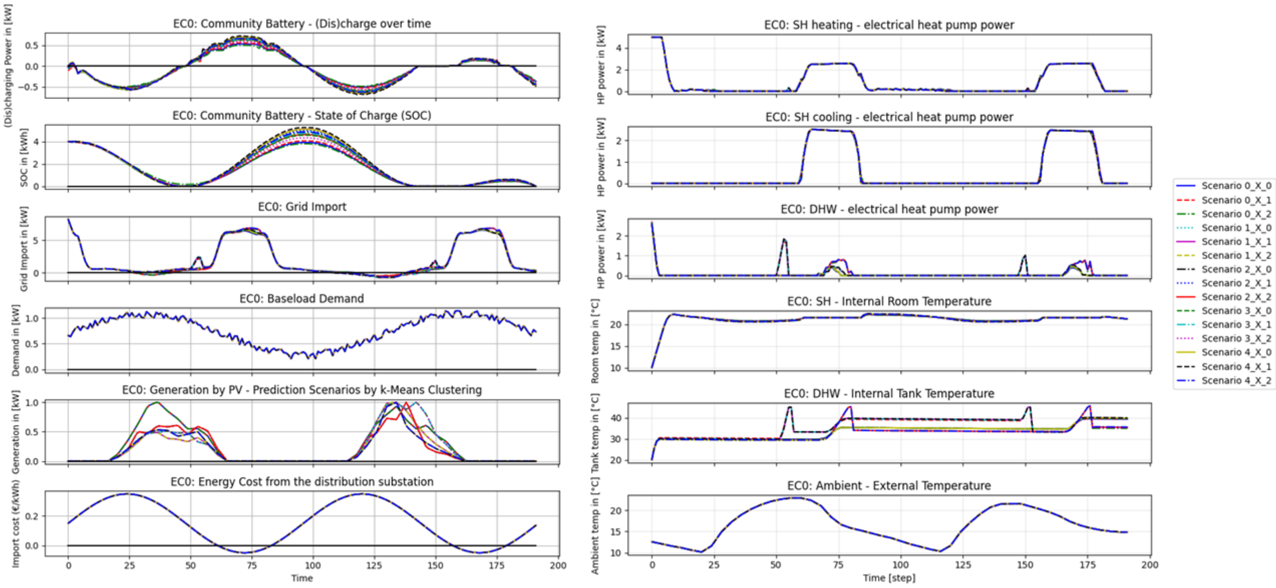

Figure 1: Power and cost in relation

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References

[1] Barabino et. al. "Energy Communities: A review on trends, energy system modelling, business models, and optimisation objectives", 2023, Sustainable Energy, Grids and Networks 36, doi: 10.1016/j.segan.2023.101187

[2] B. Herold et. al. "The Building as Energy Storage: Sector Coupling for Peak Shaving in Active Energy Communities", 2025, IEEE Kiel PowerTech, doi: 10.1109/PowerTech59965.2025.11180249

[3] P. Bacher and H. Madsen. "Identifying suitable models for the heat dynamics of buildings.", 2011, Energy and Buildings 43, doi:

[4] E. Rosert and B. Reetz. "DWD Open Data Downloader," 2025. https://github.com/DeutscherWetterdienst/downloader. [Accessed: Nov. 17, 2025].