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4.1 Market-based algorithm with local power grid feedback mechanisms

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1. Introduction

This report presents an overview of the market-based algorithm and local grid feedback mechanisms developed independently by three partner institutes within the Ecom4Future project. The overarching goal of the project is to design, implement, and validate a market-based coordination approach that can operate effectively across different configurations of local energy communities.

To support this goal, each institute has developed its own methodological framework for enabling local energy communities to act as active participants in the local electricity network. These methods aim not only to optimize local energy exchanges but also to provide valuable support to the distribution grid during periods of stress or operational need.

The following sections describe and compare the approaches taken by the three institutes, highlighting their underlying principles, modelling choices, and intended contributions to a more flexible and resilient local energy system.

2. Chalmers

2.1 Description of approach

This work proposes a distributed coordination framework between a Local Energy Community (LEC) and a Distribution System Operator (DSO) for the optimal utilization of flexible energy resources. The coordination is achieved through a hierarchical architecture consisting of three main actors: (i) flexible resources within the LEC, (ii) an aggregator acting as an intermediary, and (iii) the DSO responsible for maintaining network feasibility.

There are two levels included in the system architecture of this approach and it can be seen in Figure 1. The DSO level corresponds to the local network and the buses, and the aggregator level includes the connection points within each bus where the Local Energy Community (LEC) are connected. The LEC include residential buildings equipped with photovoltaic (PV) systems, battery energy storage systems (BESS), and electric vehicles (EVs).

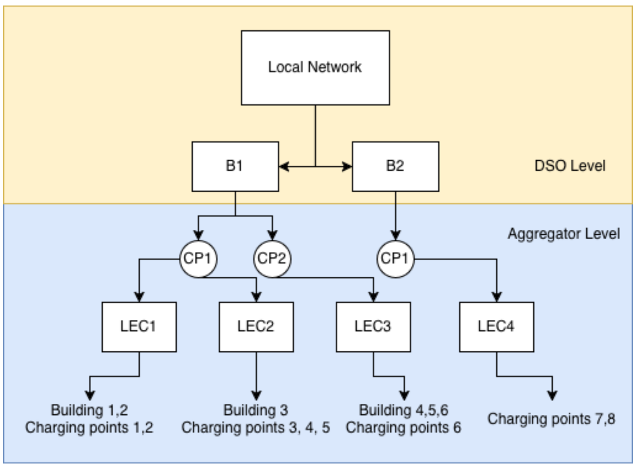

Figure 1 System architecture for Chalmers methodology

Each LEC performs a local optimization to minimize its operational cost while responding to external price signals. The aggregator collects and aggregates the power schedules from individual LEC and maps them to the corresponding network buses. The DSO evaluates the aggregated demand using a DC optimal power flow (DC-OPF) model to ensure that network constraints such as line limits are not violated.

The coordination between the LEC and the DSO is implemented using an iterative price-based mechanism inspired by Alternating Direction Method of Multipliers. At each iteration, flexibility prices are updated based on the mismatch between the aggregated LEC demand and the network-feasible solution obtained from the DSO. These updated prices are then fed back to the flexible resources, which re-optimize their schedules accordingly.

The iterative process continues until convergence is achieved, defined as the condition where the mismatch between the LEC schedules and the DSO-feasible solution falls below a predefined threshold, or a maximum number of iterations is reached. This approach enables decentralized decision-making while ensuring system-level feasibility.

2.2 Modelling details

The overall modeling approach is outlined in a flowchart, and it can be seen in Figure 2.

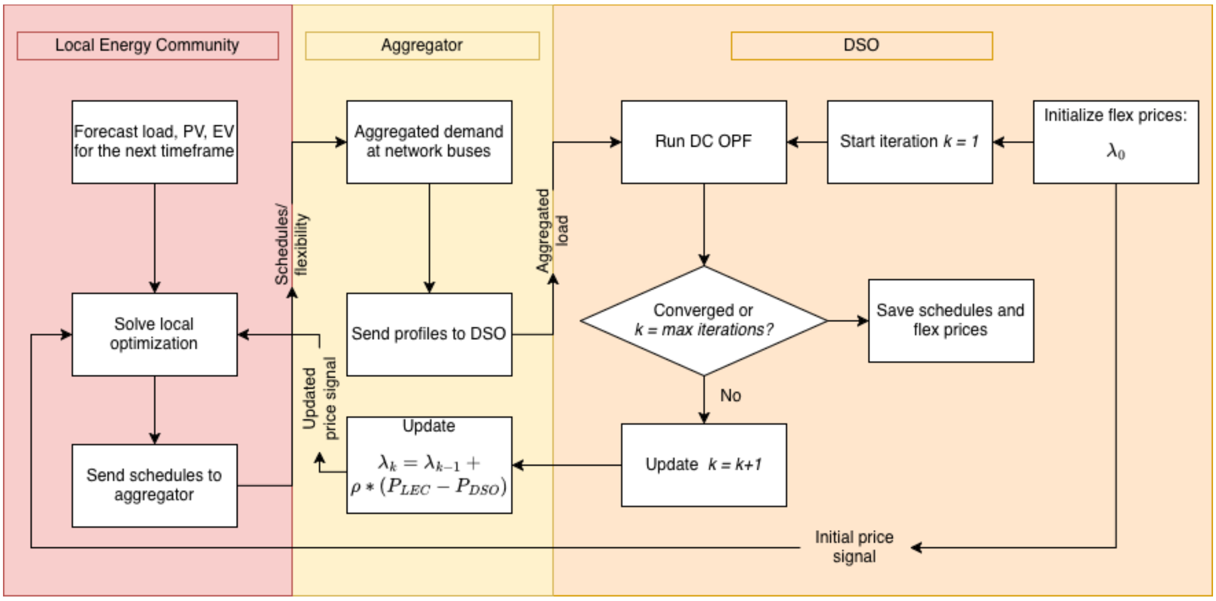

Figure 2 ADMM-based coordination for local energy community with adhering grid constraint

2.2.1 Local Energy Community Optimization

Each local energy community solves a local optimization problem over a discrete time horizon. The objective is to minimize the total operational cost, which includes electricity market costs and flexibility price signals received from the aggregator.

The optimization problem can be expressed as minimization of:

1. Energy procurement cost (based on spot prices and network costs)
2. Flexibility cost (based on price signals λ)

Subject to the following constraints:

1. Power balance constraints
2. EV charging/discharging limits and state-of-charge (SoC) dynamics
3. BESS operational constraints
4. User-defined preferences (EV departure, SoC requirements)

The output of this step is a power schedule for each resource

2.2.2 Aggregator Model

The aggregator is responsible for:

1. Collecting individual schedules from LEC
2. Aggregating power at the network bus level
3. Communicating aggregated demand to the DSO
4. Updating the flex prices after DSO solving their optimization
5. Communicating flex prices to the LEC after DSO optimization

The aggregation is performed by mapping each resource to its corresponding bus in the distribution network. The result is a vector of net power injections at each bus.

Once DSO optimization is completed the aggregator undergoes the coordination phase via ADMM where the flex prices for the next iteration are updated based on DSO optimization result and the updated flex prices are communicated to the LECs by the aggregator.

2.2.3 DSO Optimization

The DSO solves a DC optimal power flow problem to ensure that the aggregated demand is feasible within network constraints.

The objective of the DSO is to minimize system imbalance while subject to:

1. DC power flow equations
2. Line capacity constraints
3. Network topology constraints

If violations occur (e.g., line congestion), the DSO computes dual variables associated with these constraints, which are interpreted as flexibility prices.

2.3 Data Requirements

The proposed framework requires several categories of input data:

LEC data - to be trained in machine learning to forecast:

1. Load profiles for each building
2. PV generation
3. EV session data:

   a. Arrival/departure times
   b. Initial and target state-of-charge
4. BESS parameters:
   a. Capacity
   b. Charging/discharging limits
   c. Efficiency

Market data:

1. Spot prices
2. Network costs

Network data:

1. Distribution network topology
2. Line parameters (reactance, capacity limits)
3. Bus mapping for each LEC

2.4 Market aspects

The proposed framework operates as a local energy and flexibility market, where distributed resources within a LEC optimize their operation in response to dynamic price signals. Flexibility prices are iteratively generated based on network conditions evaluated by the DSO, reflecting congestion and system constraints.

An aggregator coordinates the exchange of information between the LEC and the DSO, enabling decentralized decision-making while ensuring network feasibility. This price-based coordination incentivizes flexible resources such as EVs and BESS to adjust their schedules in a system-beneficial manner.

The framework is inherently scalable and can be extended to interact with external electricity markets, allowing the LEC to both respond to spot price signals and offer aggregated flexibility services.

2.5 Current status and outlook

The model is currently under active development, building upon existing optimization model and algorithms from Chalmers University of Technology. The developed model will be tested out on Chalmers campus as part of work package 6 in this project and we will encompass the method and results of this demonstration through academic publication which will be submitted before the end of the project.

3. RWTH

RWTH follows two connected approaches for WP4. The first is the coordination of flexible resources in an ADMM-based market approach, while the second approach focuses on the building level and aims at quantifying flexibility offers for these buildings to trade in markets. The two approaches are described below.

3.1 Market-based trading flexibility

This approach addresses the challenge of enabling diverse prosumers with varying individual perspectives and values to participate in local energy communities. The key innovation lies in aligning community-wide objectives while preserving individual autonomy, complexity and preferences.

3.1.1 Description of approach

The local market employs the Alternating Direction Method of Multipliers (ADMM) with a central coordinator to minimize community costs and to account for the current grid state. The local entities focus on minimizing their own operating costs, while the coordinator aligns everyone's needs with those of the grid. This iterative process, illustrated in Figure 3 proceeds as follows:

1. Local ADMM entities (buildings consisting of heat pumps, electric vehicles, etc.) and the grid obtain their current state values.
2. Local entities run individual optimization problems to minimize their costs.
3. The ADMM coordinator updates the cost step based on aggregated information and grid state.
4. Steps 2--3 repeat until convergence is achieved.
5. Upon convergence, final power profiles are distributed and entities execute their optimized schedules.

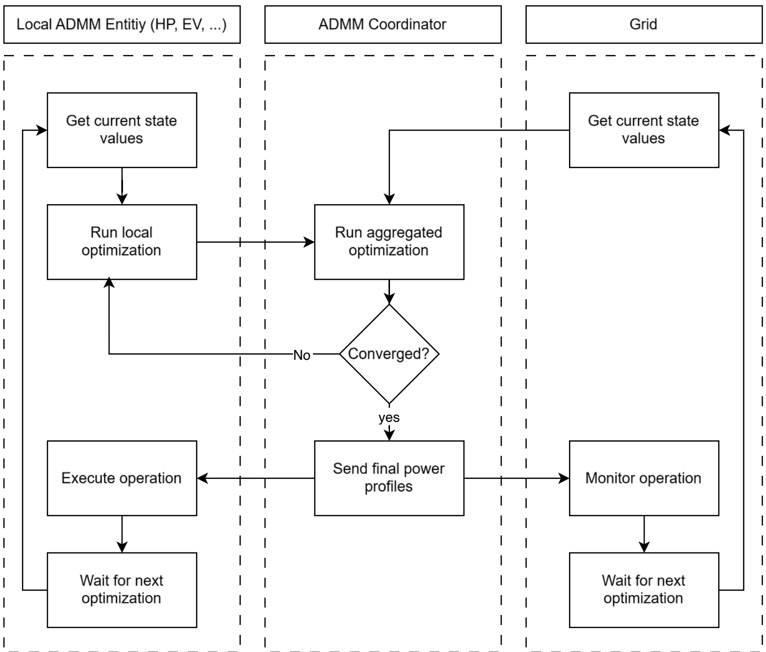

Figure 3 ADMM-based coordination flowchart for energy community optimization

3.1.2 Modeling details

The optimization framework combines multiple formulation types:

1. Coordinator optimization: Linear Programming (LP) and Mixed-Integer Linear Programming (MILP)
2. Local optimization: Nonlinear Programming (NLP) or Mixed-Integer Nonliner Programming (MINLP)

Local entities include components such as electric vehicle chargers, battery storage, photovoltaic systems, and building heating systems (thermal mass, storage tanks, and heat pumps, electric boilers).

Detailed models are utilized for the local entities. For example, the heat pump is modeled with a minimum part load and dynamic COP based on manufacturer data. Storage tanks include multiple layers, and different transfer systems such as radiators or underfloor heating can be used. The building zone is modeled as a single thermal zone using an RC approach.

3.1.3 Data requirements

Current simulations utilize physical modeling of individual homes based on building stock data combined with historical user behavior, weather conditions, and market prices. The temporal resolution ranges from 1~minute to 1~hour depending on the application.

3.1.4 Market aspects

The approach is designed to act as a local energy market that also trades available flexibility. In theory, if the energy community is sufficiently large, external spot markets (e.g., the German spot market) could be integrated as well.

3.1.5 Current status and outlook

The model is currently under active development, building upon existing optimization models and algorithms from RWTH Aachen University. The codebase will potentially be published through academic publications. Due to the absence of physical demonstrators, validation is limited to simulation studies. This work relates to project tasks 4.2 and 4.3, with potential adaptations for task 4.1.

3.2 Quantification of flexibility offers

This approach addresses the challenge of enabling individual prosumers to actively quantify and price their available flexibility during operation, creating standardized flexibility offers that can be traded in local or aggregated markets while preserving the privacy and individual preferences of participants.

3.2.1 Description of approach

The FlexQuant methodology enables prosumers to generate flexibility offers through three Model Predictive Controllers (MPCs). The process, illustrated in Figure 4 proceeds as follows:

1. The building runs a Baseline MPC to determine optimal normal operation.
2. If no active/accepted offer exists, Shadow MPCs are executed to predict possible deviations from the baseline. These shadow MPCs do not interact with

the actual building and just forecast potential flexible operations within the comfort boundaries specified.

3. Flexibility offers are calculated based on the difference between baseline and shadow MPC power trajectories.
4. Flexibility offers, consisting of activation time, power profiles for baseline and flexible operation, and associated costs, are communicated to the market or possible a coordinator of an ADMM as described in Section 3.1.
5. Upon receiving feedback, if the offer is accepted, the baseline is adapted to follow the promised power profile.
6. The system then waits for the next cycle.

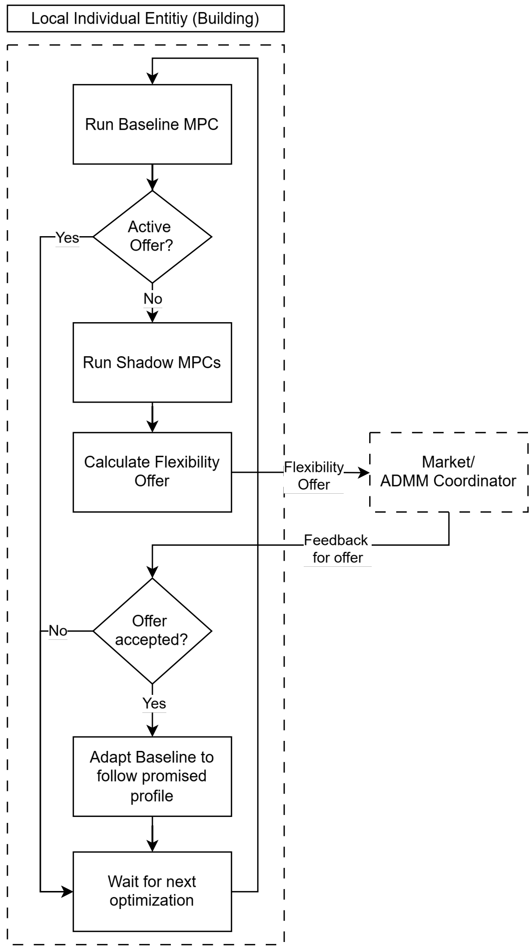

Figure 4 FlexQuant flowchart for flexibility offer quantification in buildings

A key feature of this approach is that only the flexibility offer is communicated externally, preserving the privacy and individual autonomy of each participant. The market mechanism itself is not modeled within this approach but is addressed separately, allowing flexibility offers to be accepted based on various algorithms.

3.2.2 Modeling details

The local flexibility quantification employs Nonlinear Programming (NLP) or Mixed-Integer Nonlinear Programming (MINLP) for the MPCs used. The Baseline MPC aims at minimizing operating costs for the prosumer, while the shadow MPCs aim at maximizing or minimizing power consumption respectively.

Constraints are related to flexible resources and user comfort requirements. More details on this approach are given in [1].

The modeled flexible resources include battery storage, photovoltaic systems, and the heating system of the building. The models used are the same as the ones used for the local entities in Section 3.1.

3.2.3 Data requirements

Current simulations utilize physical modeling of individual homes based on building stock data combined with historical user behavior, weather conditions, and market prices. Input data includes flexible resource parameters, market prices, and user preferences. The temporal resolution ranges from 1 minute to 1 hour depending on the application.

3.2.4 Market Aspects

The approach is designed to participate in local energy markets and local flexibility markets. Rather than developing new market structures, this approach enables participation in existing and emerging market structures by creating standardized flexibility offers. This requires an Energy Management System with MPC capabilities for local prosumers.

3.2.5 Current status and outlook

Initial publications on this model are available [1] with further papers planned. Current development focuses on investigating the most important resources for flexibility offers in buildings and exploring additional use cases. While primarily a simulation-based approach, application to a Hardware-in-the-Loop heat pump test bench is currently under development. This work relates to project tasks 4.2 and 4.3, with potential adaptations for task 4.1.

4. DWH

Within WP4, DWH GmbH focuses on the development of optimization methodologies for Energy Communities (ECs), aiming to reduce operational costs and optimize energy flows.

4.1 Modeling structure

The proposed approach consists of two main components: (i) forecasting of energy consumption and photovoltaic (PV) production as basis for (ii) optimization of energy usage using Reinforcement Learning (RL). The forecasting results serve as input for the optimization framework. The main steps of this process are outlined in Figure 5.

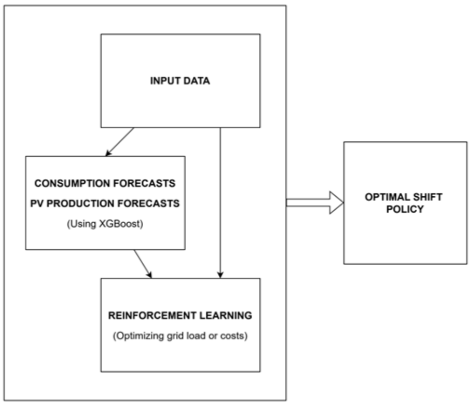

Figure 5 General workflow of DWH

The methodology is evaluated using a real-world trial site in Niedergrail, consisting of five participants, of which two are equipped with PV systems and battery storage.

4.1.1 Forecasting method

For the forecasting component, several external data sources were integrated to improve prediction accuracy. Weather data, particularly solar irradiance and temperature, was essential for PV generation forecasting. Time-related features were transformed into a continuous representation using sine and cosine encoding to capture daily and seasonal cyclic behavior.

After preprocessing, a range of time series forecasting approaches were evaluated, including statistical models (ARIMA, SARIMA, SARIMAX) as well as machine-learning-based methods (XGBoost, Random Forest Regression, Support Vector Regression, K-Nearest Neighbors). Based on performance evaluation, XGBoost was selected due to its predictive accuracy and robustness.

To ensure compatibility with the RL framework, a direct forecasting approach was implemented to predict a 24-hour horizon, since this is a realistic horizon to optimize for. This is achieved by training multiple models to directly estimate future values for each time step, enabling efficient integration into the optimization process.

4.1.2 Reinforcement learning based optimization

Reinforcement Learning (RL) was applied to optimize energy consumption and cost reduction strategies within the energy community. While RL offers wide flexibility and the potential to discover non-obvious control policies that might not emerge from classical optimization methods, it requires large amounts of training data and long computation times. In addition, the resulting models can be difficult to interpret due to their black-box nature.

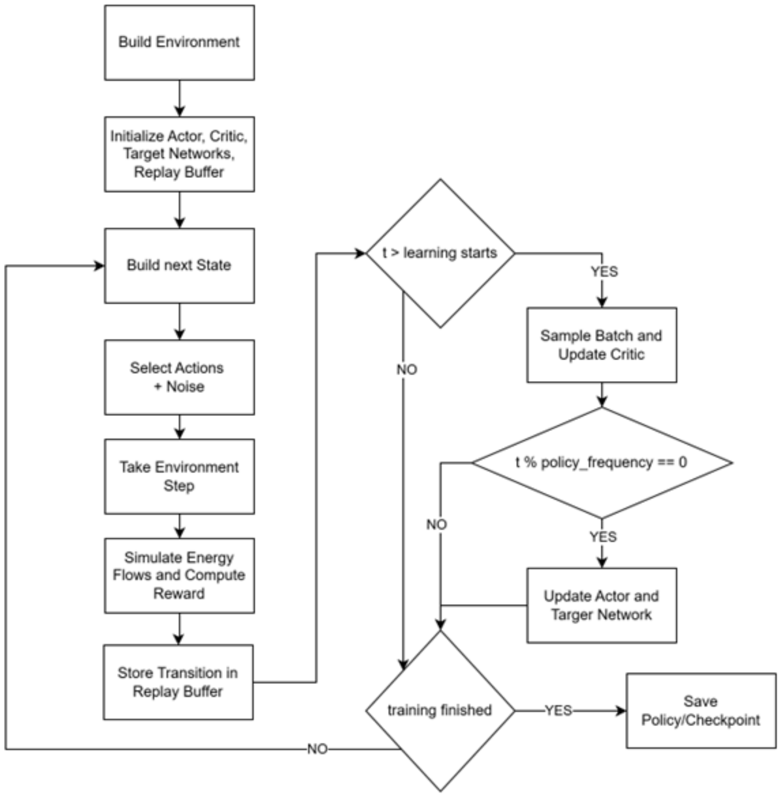

Figure 6 Flowchart of RL algorithm

The general structure of the RL approach is displayed in Figure 6. As an initial step, we focused on a single participant of the energy community. The first optimization objective was to minimize grid load. Subsequently, grid price information was introduced, and the objective was extended to minimizing energy costs for the participant. The policies learned by the RL agent were evaluated against both a rule-based baseline model and the actual operational behavior observed in the energy community.

In a further step, the approach was extended to a Multi-Agent Reinforcement Learning (MARL) framework. This allows multiple participants to interact and coordinate their behavior, potentially improving overall system performance. To facilitate flexibility, the model incorporates configurable variables that define, prior to each run, which resources (battery and PV energy) agents are allowed to share, and which are restricted. This allows different sharing strategies to be simulated within the same environment without modifying its underlying structure. In practice such coordination may face regulatory constraints in real-world applications. Nevertheless, this setup provides valuable insights into the potential benefits of increased flexibility within energy communities.

4.2 Data requirements

Both forecasting and optimization rely on several data sources.

4.2.1 Energy community data

The data from the energy community includes:

1. Load profiles for each household (participant) of the EC
2. PV generation (of all participants in possession of a PV system)
3. Battery load profiles (of all participants in possession of a battery)

All these are given in 5-minute or 15-minute intervals, depending on whether they have a PV/battery or not. Because other, external data are available in 10 minute and hourly resolution, the energy community data are aggregated into 10-minute granularity as well as hourly data for comparison reasons.

4.2.2 External data

The extrnal data includes:

1. Weather Data (10 minute granularity):
    a. Global Radiation (cglo)
    b. Temperature (in 2 meters hight)
2. Grid Prices (hourly granularity):
    a. Electricity Costs
    b. Feed-in tariff

All data sources used here are open source and can be obtained from the follwing websites:

1. https://data.hub.geosphere.at/
2. https://www.awattar.at/tariffs/hourly

4.3 Market aspects

The proposed approach is designed to enable participation in local energy and flexibility markets. It supports integration into existing and emerging frameworks by providing optimized and data-driven strategies for load shifts.

The developed RL framework allows the exploration of extended operational scenarios, such as shared use of flexible resources (e.g., battery storage) across participants. While such coordination may currently be limited by regulatory constraints, it provides valuable insights into the potential benefits of increased flexibility and resource sharing within future energy market designs.

4.4 Current status and outlook

The forecasting component has been completed and is now used as input for the RL framework. Both participants of the Energy Community in Niedergrail have been integrated into a modeling framework that enables RL-based optimization, targeting either grid load reduction or cost minimization.

Currently, hyperparameter optimization is being carried out to further improve the performance of the RL agents. In addition, an initial version of a Multi-Agent Reinforcement Learning (MARL) framework has been developed to model interactions between participants.

Similar to the single-agent setup, further tuning of hyperparameters is required for the MARL approach. Moreover, the definition of constraints -- particularly with respect to the shared use of battery storage and PV generation -- remains an open task and will be refined in the next phase of the project.

In order to evaluate the Reinforcement Learning based optimization approach regarding its applicability in Energy Communities, it will be compared to conventional optimization approaches implemented by other project partners in the further course of the project. The results of this comparison will be documented and submitted to a conference by autumn 2026.

5. Bibliography

[1] F. Stegemerten, S. Leidolf, P. Stoffel und D. Müller, „Exploring flexibility in building energy systems: Agent-based quantification and electricity tariff impacts," *Energy and Buildings,* 2025.