A Framework for Strategy Selection of Atomic Entities in the Holonic Smart Grid

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***Abstract*—Maintaining the continuous supply of electricity within smart microgrids is a challenging task, which becomes increasingly difficult with the growing integration of volatile Renewable Energy Sources (RES). Quick changes within the production behavior of these resources can disturb the necessary balance between demand and supply and may ultimately lead to blackouts within the grid. To prevent balance disturbances, electricity production and consumption needs to be coordinated and power needs to be shared among the participants within the microgrid. Facilitating coordinated behavior of grid entities and ensuring reliable operation of the microgrid in the presence of volatile RES requires sophisticated strategies for operating individual participants. In this paper, we present a modular framework to support dynamic energy distribution for atomic entities (producers/consumers) in holarchically organized energy grids. In particular, the framework provides production and consumption forecasting to enable intelligent strategy selection to improve the day-ahead control decisions for atomic entities. The proposed framework enables the bottom-up formation of smart mircogrid holons and represents a foundation for the formation and strategic coordination of participants in smart microgrids.**

Keywords*—*Micro Grids; Holonic Smart Grids; Optimization; Forecasting; Strategy Selection.

I. Introduction

Electrical grids are evolving from a centrally managed critical infrastructure to distributedly managed Smart Grids (SGs). This evolution is driven by the need for the grid to incorporate local production capabilities of renewable Distributed Energy Resourcess (DERs). The paradigm shift from centralized to distributed control, however, leads to a considerable increase in the complexity of network management tasks. Various approaches for tight monitoring and fast control have been put forward to support continuous operation and provide stability of distributed energy grids [1]–[3]. These approaches generally rely on strong support by Information and Communication Technologies (ICT).

Hierarchical and cellular network segmentation promises to simplify the mechanisms for controlling the SG. The next evolutionary step for cellular network approaches are *holar* structures [4]. In particular, these systems seek to leverage formation and segmentation by enabling the reuse of mechanisms on different hierarchical levels. Entities in such a system (so-called Holons) are simultaneously a "whole" and a "part" of something bigger. The emerging system-of-systems structure is referred to as a holarchy [5]. Holons are dynamic cells, which can merge with other holons (or separate into individual smaller ones) when suitable. Under optimal conditions, holons tend to form larger holons, while their capability to separate sub-parts aids in increasing network stability (e.g., by splitting off potential misbehaving or faulty entities). This is ensured cause holocharies are mainly based on the concepts of *isolation* and *containment* [6].

In this work, we consider single buildings, be they commercial or residential, to be the atomic building blocks of holons. With the integration of DERs, they may be both producers and consumers, so called *prosumers* of energy. In order to facilitate holon creation and stable operation, particularly in small-scale grid scenarios, accurate models for the behavior of these prosumers are necessary. This, in turn, entails the need for a framework that is capable of forecasting, within reasonable limits, both electrical load and production behaviors. This need is exacerbated especially in small holons, i.e., smart microgrids, because smoothing effects on energy production and consumption are not as effective here as in larger grids.

Based on the considerations mentioned above, we present a framework for stable holon operation. In particular, at an atomic prosumer level, the framework consists of a consumer, production unit, storage system and a power supply. The main contributions of the proposed framework are:

- Provision of dynamic control via smart strategy selection for holonic smart microgrids.
- Advancement of current smart microgrid capabilities by enabling forecasting and operation optimization on the level of atomic holons.
- Showcasing the applicability of the current deployment of the framework by deploying it at a real-world prosumer site.

The rest of the paper is structured as follows: Section II describes the topology and power flow of an atomic holon, as well as the conceptual framework model and information transmissions. In Section IV, further details concerning the forecast model and operation strategy optimization are provided. We finalize this work with conclusion and future works in Section V.

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II. SYSTEM

The goal of this section is to present the system description of an atomic building block of holons and the energy flow between the different components. Following this, the structure and information flow of the framework is detailed.

A. Topology

To manage the merging and splitting process of a holon, an optimized energy flow at the atomic level, i.e., for individual consuming and producing participants, is necessary. Therefore, the individual components that are encompassed in an atomic holon require a clear definition. Figure 1 shows the four components of what we treat as an atomic holon: *consumer*, *producer* (PV), *storage* (batteries) and *power grid*. An atomic holon can, but does not need to, implement all components. The arrows indicate the direction of possible energy flow.

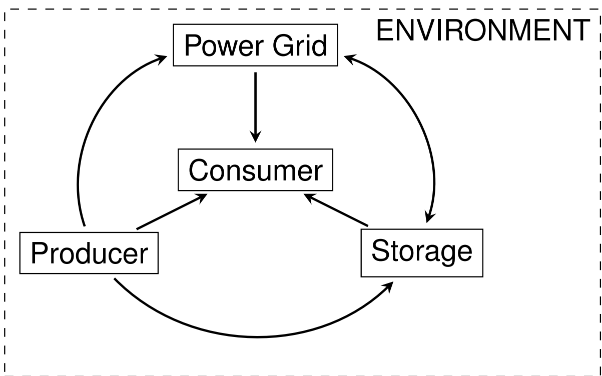

Figure 1. Energy flow between the four different holon components.

a) Power grid: The grid-connected power supply of the building. Ideally, the household's load is covered by batteries and direct consumption of self-produced energy (e.g., solar panel). In case of an increased demand, which cannot be compensated by the locally available resources, the remaining difference is taken from the general power grid.

b) Consumer: The total aggregated energy consumption of an atomic holon (This includes potential incident consumption that results from the battery storage, the solar panel and the grid connection).

c) Producer: As mentioned in Section I, every entity in the grid, which is capable of supplying electricity to itself or others is considered as an energy producer. As holons are envisioned to represent prosumers in the future energy grid the *producer* component represents the aggregated production capacity of the holon. For instance, single households with solar Photovoltaic (PV) cells or commercial buildings with wind turbines.

d) Storage: A main enabler for the efficient use of Renewable Energy Sourcess (RESs) is their combined used with an energy storage system. Aside from storing excess energy during times of high production (e.g., sunny days at noon), energy storage solutions are used to compensate for the volatile behavior of RESs. The resulting inconsistency of production behavior of RESs – due to intermittency of weather conditions – or daily consumption variations can be mitigated using energy storage systems. In general, these storage systems can consist of any type of batteries, including the batteries of attached electric vehicles.

B. Framework

The proposed framework aims to optimize control strategies in systems that are structured according to the *holarchy* concept. In particular, we focus on system control of atomic holons within a holarchy. For these holons, the following characterizations are necessary [6]:

- *Autonomy*: As holons are, simultaneously a *part* and a *whole* within a system and they may have individual goals that may differ from the general goals of the system as a whole. A holon's *autonomy* property describes its striving to fulfill its own objectives. For this, it is capable of making decisions and to create and manage the execution of its own plans and strategies.
- *Self-contained*: Each holon is a *whole* itself and can exist or work without external input by exploiting its own resources.
- *Co-operation*: Holons can cooperate on the basis of special communication and interaction rules. Holons can cooperate with other holons on similar levels within a holarchy. Additionally, they can merge with other holons to form larger holons or split into smaller holons. This concept of cooperation enables holons to achieve more complex goals (e.g., due to more available resources after a merging process), and enables to interrupt the cooperation by isolating faulty parts.

In order to facilitate holarchical operation in a better way, the proposed framework uses a bottom-up approach. Instead of organizing holons with a top-down approach, this framework regulates the strategic operation within an atomic building block, composed of the previously described system's primary components. In future work, we will expand the prediction and strategy selection to non-atomic holons.

The framework architecture can be seen in Figure 2. It is divided into three main parts: *Forecasting of Resources for Dynamic Optimization (FRODO)*, *Optimal Load and Energy Flow (OLAF)*, and *Environment*. As depicted in the architecture layout, the framework works based on historical data of power consumption as well as production. Dashed-line arrows indicate the flow of information between the framework components. FRODO receives historical data and derives two forecasts: PV production and load consumption. Information about these two forecasts, in addition to information about the holar system structure, are then used by OLAF as an input for the *strategy selection process*. This selected strategy is the foundation for next days charging and discharging schedule of a storage unit within an atomic holon. After considering the related work in the following Section III, Section IV provides detailed information for the individual parts of the framework.

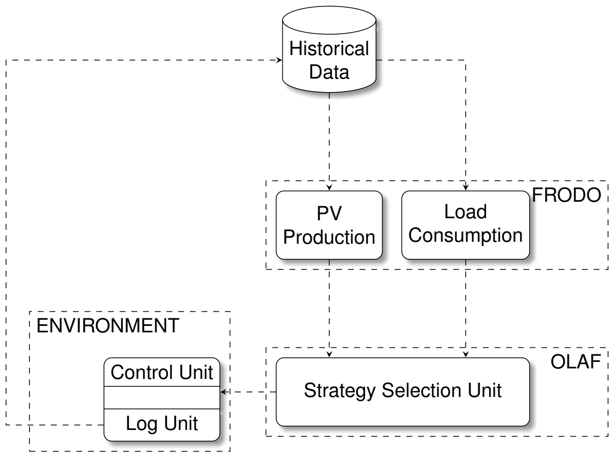

Figure 2. Structure and information flow within the Framework.

III. Related Work

In related work, Battery Energy Storage Systems (BESSs) for handling fluctuations in DER are a major research topic. The requirements of a BESS for mitigating PV output fluctuations are examined in [7]–[9]. In [10], a control scheme for energy devices in the distribution network to reduce peak demand based on day-ahead demand forecasts is presented. Thereby, the research focuses on optimizing the storage system's schedule from the network operator's perspective. [11] proposes a solution for finding the optimal size of a BESS with regard to economic perspective, which can be used in addition to finding the optimal charge and discharge strategy under certain conditions. In [12], a day-ahead energy management framework of a microgrid is presented; the authors propose management of the energy flow based on next days electricity price. That is one possible strategy for controlling the energy flow. In this work, we are defining several strategies and looking for the best based on external constraints. Batteries are also used in [13] to maximize a households profit. Control strategies are applied for scheduling electric vehicles to implement peak-shaving and valley-filling in [14]. In this scenario, the electric vehicle takes part of a storage unit in Figure 1.

IV. Methods

The promising results in BESS-oriented related work suggest the potential of prediction-based strategy selection for the dynamic creation of holar microgrids. The framework proposed in this paper aims to leverage these results and, in future work, also to integrate formation and control methods for merging and splitting holar microgrids.

This section gives detailed information for the three different parts of the framework: *Historical Data* (IV-A), *FRODO* (IV-B) and *OLAF* (IV-C). Additionally, we show the first results on day-ahead load forecasting based on real-world data.

A. Historical Data

The load consumption and PV production data used in this paper are provided by the *Technology Centre of Energy (TZE)* at the Landshut University of Applied Sciences. The load consumption and PV production data was collected from January 1st, 2017 to December 31st, 2018 and are available for every minute. However, in this paper we are using 60 minutes – or hourly – discrete power values for production $[\mathrm{kW}]$ as well as consumption $[\mathrm{kW}]$. Weather data are recorded at the stationary installed weather station at the TZE for *temperature* [°C], *humidity* [%], *solar irradiation* $[\mathrm{W/m^2}]$, *precipitate* $[\mathrm{mm/min}]$, *wind speed* $[\mathrm{m/s}]$, *wind direction* [°] and *air pressure* $[\mathrm{hPa}]$. Missing weather data points are taken from the *Deutscher Wetterdienst (DWD)*.

To ensure valid forecasting results by FRODO, the following data preprocessing steps are implemented:

- Data cleaning: To reduce the influence of missing data, interpolation was executed if the gap is less than one hour. Otherwise the average value for the specific time-slot was scaled to fit the curve. Since we are doing day-ahead forecasting, days without previous load consumption are also removed.
- Time-series to supervised learning: The raw data is a time-series sequence ordered by a time index for every minute, which is first aggregated to hourly discrete values and then converted to input-output-pairs (x_n, t_n) where x_n are the inputs and t_n the output values for each day $n = 1...N$.
- Input selection: Feature engineering is a crucial task in machine learning. Figure 3 shows the daily average power consumption per weekday and there is a significant difference between workday and weekend visible. Therefore, the date features are *one-hot-encoded*, i.e. 1000000 for Monday, 0100000 for Tuesday and so on. The same applies to special days like *holidays*.

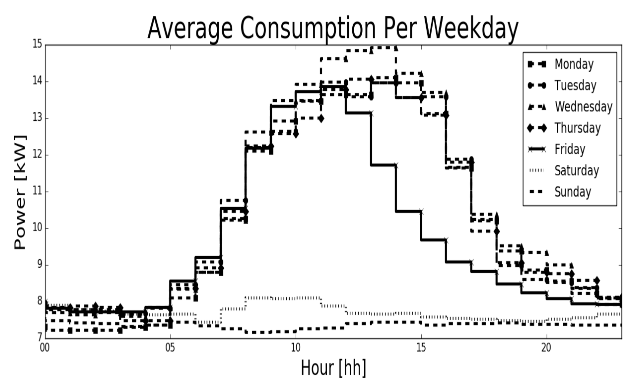

Figure 3. Daily average consumption per weekday over a 2-year period.

For illustration, Figure 3 depicts the daily discrete power values for consumption over a day divided into 23 hourly intervals. Beside the previous mentioned difference between workday and weekend, there is a clear decrease after Friday lunchtime visible. This is explained due to the fact that the *consumer* in this show-case is formed by a research center with around 15-20 employees working regularly on weekdays. The *production* unit in this research is a $10.4\ \mathrm{kWp}$ installed PV

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module and different batteries, e.g., 100 kW h Redox-Flow, 125 kW h Lithium-Ion, 12 kW h Lithium-Ion, are used as *storage* systems. These are the key components for the atomic holon in this show-case as well as the consumption data – and also the production data – which provides the basis for the forecasting module, described in the following part.

B. FRODO

To ensure an efficient energy flow between the different entities within a holon, a precise load consumption and PV production forecast is essential. Due to page limitations, only the development process for the load consumption component within FRODO is described. The PV production forecasting works similarly and will be shown in subsequent work. Different forecast approaches can be classified according to their forecast horizon. Hereby, we differentiate between three main categories: *Long-Term Load Forecast* (1 year to 10 years ahead), *Medium-Term Load Forecast* (1 month to 1 year ahead), *Short-Term Load Forecast* (1 hour to 1 day or 1 week ahead) [15]. A main requirement for using the proposed framework is to be able to dynamically select the next day's operation strategy. For enabling this, a Short-Term Load Forecast (STLF) is essential. Therefore, two different Machine Learning (ML) models for STLF are developed and tested against each other: A first model leverages *Random Forest (RF)* and the second one is based on a *Long-Short-Term memory (LSTM) neural network*. Both approaches have been tested and proven to work well for the present forecasting task in the related literature [16]–[19].

Architecture: The RF is an ensemble method that operates by constructing a multitude of decision trees whereby each tree forecasts the load consumption by itself and the method returns the mean value. In this case, 500 trees are created at training time with a maximum depth of 15. The LSTM is a recurrent neural network and unlike standard feedforward networks, LSTM has feedback connections to maintain information, which is used for solving learning tasks based on prior input data and decisions [20]. We use one hidden layer with 50 neurons, one dropout layer with 0.2 rate to avoid over-fitting and one dense layer with 24 neurons, since we want forecast values for every hourly interval. The prior mentioned hyperparameters of each method are estimated through extensive *grid search*. For that reason, the historical data are first split into three distinct groups: *training* (80 %), *validation* (10 %) and *test* (10 %). The first two are used for tuning the previously mentioned hyperparameters. After estimating the best model architecture, each model is tested by using a *10-Fold Cross-Validation*.

Input Features: In [21], we showed that the power consumption for an exemplary day d can be explained by the consumption values of the previous day $d-1$ and by last week's consumption $d-7$. In addition, we mentioned previously the importance of calendric factor like day of week and holidays. Therefore, the input features are composed of the following 58 variables: (*Input* $1-24$) consumption of $d-1$ [kW], (25) mean temperature T_{d-1} [°C], ($26-50$) consumption of $d-7$ [kW], (51) mean temperature T_{d-7} [°C], ($52-57$) one-hot-encoded day of week and (58) holiday [0 or 1]. Training, validation and test data are input-output pairs (x_n, t_n), with $n = 1...N$, where x_n are the explanatory input variables and t_n the outputs.

Evaluation: The test data is used to evaluate the model's forecast accuracy. Therefore, the third split of the historical data was held back to measure the model's accuracy on "unknown" input data. Figure 4 shows next day's consumption forecast of both RF and LSTM for one example day, and also the actual measured values for comparison. It shows good accuracy in the morning as well as in the evening, but a clear underestimation for the three intervals between 11 and 14 o'clock. This behavior is caused by the fact that those consumption values are way above average (see Figure 3) and can not be handled well by both RF and LSTM. To improve this forecast behavior, further model adjustments are done in future work described in Section V.

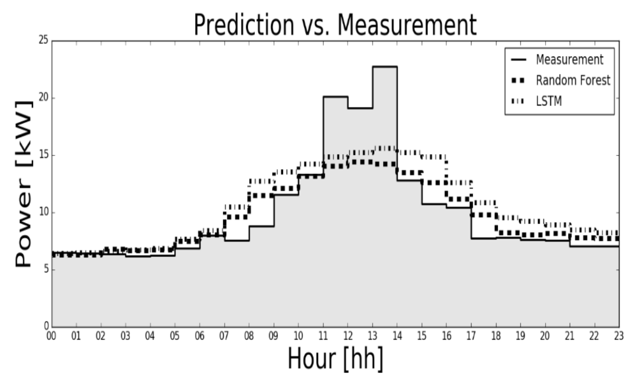

Figure 4. Forecast values and actual consumption for one example day.

For model comparison, three different persistence approaches are used. Let $L(d, h)$ be the consumed load for a specific day d at a particular hour h. A persistence model is a method to predict the future behavior on the assumption that current load consumption $L(d_t, h)$ is similar to the value at the same hour of a different day $L(d_{t-i}, h)$. The following approaches are implemented: (1) *"previous day"* $L(d_t, h) = L(d_{t-1}, h)$, (2) *"last week"* $L(d_t, h) = L(d_{t-7}, h)$ and (3) *"weekday average"* $L(d_t, h) = \overline{L(d_t, h)}$, where $\overline{L}$ denotes the average value for a specific day and hour.

To quantify the results numerically, forecast accuracy is presented using standard measures: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Percentage Error (MPE), defined in the following equations Eq. (1)–(4):

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(Y_n - \widehat{Y_n})^2 \quad (1)$$

$$RMSE = \sqrt{MSE} \quad (2)$$

$$MAE = \frac{1}{N}\sum_{n=1}^{N}\left|Y_n - \widehat{Y_n}\right| \tag{3}$$

$$MPE = \frac{100\,\%}{N}\sum_{n=1}^{N}\left(\frac{Y_n - \widehat{Y_n}}{Y_n}\right), \tag{4}$$

where Y_n represents the actual value of the electrical load and parameter $\widehat{Y_n}$ is the corresponding forecast value, respectively. N is the sample size. The forecast results on the test set are given in Table I.

TABLE I. RESULTS OF MEASUREMENTS FOR DIFFERENT CONDUCTED FORECASTS

Model	MSE	RMSE	MAE	MPE
Previous Day	15.82	3.98	2.46	-6.51
Last Week	9.27	3.04	2.16	*1.45*
Weekday Average	5.42	2.33	1.77	-3.39
RF	*4.86*	*2.20*	*1.43*	-1.57
LSTM	6.23	2.45	1.67	-4.29

The results in Table I show that the RF has an increased forecast accuracy compared to the persistence approaches and that the LSTM performs worse than the “weekday average” persistence models. For every metric, the lowest value is the best result and is indicated by emphasized cells. It is also worth mentioning, that the forecast error for the RF remains mostly constant regardless of the different splits of the data set. In contrast, the LSTM results depend highly on the segmentation of training and test sets. This might be due to the LSTM overfitting of the data based on the distribution of workdays, weekends and outliers (way above average days). Due to page limitations, this section only describes the load consumption forecast. However, the production forecast (e.g., solar, wind) works similarly and will be the focus of further work. The derived energy production and consumption forecasts are further processed by OLAF, where the optimal strategy for the energy flow between the different holon components is selected. This selection process and also definitions of example strategies are explained in the following section.

C. OLAF

The OLAF module of the framework is responsible for selecting and executing the next day’s operation strategy. Basically, this strategy is a sequence of information how and in which direction the energy flow between the components (see Figure 1) is realized for each next day’s hourly interval. This includes schedules for charging and discharging the storage unit, based on some prior defined constraint and optimization goals, which are specified in the following paragraph. For this, OLAF receives the two previously generated PV production and load consumption forecasts of the FRODO module and selects a BESS operation strategy based on this information. The different possible BESS strategies can roughly be divided into three categories: *customer-*, *market-* and *grid-oriented* strategies [22]. A more detailed classification for operation strategies is presented in [23]. These strategies and the primary beneficiary are defined as follows:

- *Maximized consumption of self-generated power* (customer): Produced power is primary used to cover the household’s load. Overproduction is going to the storage unit.
- *Limited power grid feed-in* (grid): Cuts off power feed-in at a given upper boundary.
- *Time-scheduled (dis-)charging* (grid/customer): The storage, e.g., Battery, is only used at certain time of days.
- *Time and power constrained storage* (grid): Minimize feed-in at given peak-hours for grid relief through empirical knowledge.
- *(Dis-)charging depending on energy pricing* (market/customer): This strategy’s goal is to minimize the electricity price for a given household.
- *Incremental grid relief* (grid): Instead of feed-in as much produced power as possible, only a fixed percentage is used, e.g., $30\,\%$.
- *State-of-Charge dependent charging* (customer): The charging schedule is prepared, depending on the battery’s State Of Charge (SOC). The lower the SOC, the more produced power is used to charge the battery.

The *Strategy Selection Unit* encompassed within OLAF chooses, based on the forecast values and the desired holarchical organization, a preferred operation strategy. Since we are getting next day’s forecast as hourly intervals from FRODO, the chosen strategy is executed also in hourly time steps. Subsequently, the *Control Unit (CU)* – an independent controlling element implemented in the environment – is responsible for executing the a-priori defined charge and discharge schedules for the respective storage systems (e.g., batteries) within each time interval. If the available energy does not satisfy the chosen strategy, e.g., discharge an empty battery or feed-in produced power although the limit is reached, the *Control Unit* attempts to adjust the next time interval – using the feedback loop – so that the desired goal can be achieved.

Although the *Log Unit (LU)* as well as the *CU* are not explicitly part of OLAF, they are both in communication with each other at the end/beginning of each time interval. One key function of the CU is to give feedback to OLAF, not only for strategy monitoring reasons, but also to adjust the forecast results from FRODO. If the forecast value for a time slot exceeds some threshold – both directions: overestimation or underestimation – the CU informs OLAF to modify the remaining daily values. Furthermore, the LU is responsible for logging and storing the energy data, the recorded weather data (either through a stationary station or external sources) and the operational data on a daily basis. This information is then stored as historical data and can then used by the FRODO module to improve the forecast accuracy for subsequent days,

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if the desired accuracy is not fulfilled anymore. This possible improvement – either update the forecast values or change the actual operation strategy – represents an ability to dynamically handle uncertain behavior, as it is necessary for the safe and resilient operation of energy grids base on the concept of holarchies and for performing the characterization described in Section II-B. Through smart strategy selection, e.g., *self-containment* for one atomic holon or *co-operation* between multiple atomic entities is achievable.

V. Conclusion

In this paper, we introduced a framework to provide dynamic control for the state-of-the-art holonic smart grid. Based on a bottom-up approach, the proposed framework enables holarchical organization at an atomic level. The presented approach is designed to improve current Smart Grid capabilities by providing a modular structure for forecasting and optimization. Based on historical load data, our framework makes a day-ahead forecast for load consumption and PV production, within reasonable limits. After analyzing the historical data (Section IV-A) an LSTM approach, which is an established ML technique, is presented in Section IV-B as the STLF model within FRODO. Due to page limitations, the PV production forecast was not presented in this research paper, but works similarly to the load consumption forecast and will be described in further works. To validate the load forecast accuracy, an RF and an ML technique are evaluated and compared, as well as the following three persistence models: previous day, last week and average weekday value. The results showed that both LSTM and RF are practicable methods with higher accuracy than the persistence approaches. The derived forecast values are the basis for OLAF, the optimization part within the framework, which selects the strategy for next day's energy flow within a holon. This operation strategy is chosen under predefined constraints, e.g., customer-oriented, market-oriented, grid-oriented, and is executed in one-hour-intervals over the next day. The framework is capable of handling uncertain behavior and divergent forecasts through a feedback-loop after each interval.

In future research work, we are improving the forecast models by adjusting the different ML techniques. Furthermore, we are defining more strategies to optimize the holarchical operation.

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