Simulation-based methodology for optimizing Energy Community Controllers

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***Abstract*—In recent years, the trend to provide more and more energy from renewable sources and less from conventional forms of electricity production reduces worldwide carbon emissions. In general, this is welcome but it also introduces new challenges. The diversity of electrical energy production grows and puts stress on the grid, its operators, and energy distribution planning. New ways for compensating the introduced instabilities are needed. Energy communities can address distributed production issues by adjusting the local demand as good as locally possible. This paper presents a methodology for simulating an energy community controller to test mechanism for smoothing grid load by aggregating available flexibilities of energy community members on a communal level. The controller tries to minimize load from or to the community by using different flexibilities and prediction algorithms within the community.**

***Index Terms*—Energy management, Smart Grids, Batteries, Photovoltaic systems, Machine learning, Prediction methods**

I. Introduction

Power grids are changing by the minute to cover for new challenges that arise from new technologies and the growing demand for clean, carbon emission-free energy. In recent years the amount of energy provided by conventional power plants decreases, making a place for renewable forms of energy. The nature of many forms of renewable power plants is that they provide energy depending on many different conditions like daytime, weather, and temperature. Distributed renewable energy forms introduce issues in distributing the energy to the consumers as the grid's topology is a top-down approach. There are times with excess energy production and also times where the production is at a low. Additionally, demand and production locations differ at certain times. The European Union's (EU)' Clean Energy for All Europeans Package' is an update for the EU's energy policy framework [1]. In this package, the European directive [2] lays down the basic rules for renewable energy communities and [3] for citizen energy communities. The member states are responsible for transforming them into national legislation until mid-2021. This legislation enables households and small to medium-sized businesses to participate in renewable energy communities. A way to cover for the inhomogeneous production and consumption is to use already existing flexibilities. These flexibilities range from unused battery capacities to adaptable loads like heat pumps or water pumps and electric vehicles (EVs). To use flexibilities, a controller can orchestrate the process. It covers flexibility aggregation, predicts future consumption, handles members, applies different control strategies, and communicates with other communities or grid operators to ensure grid stability. There exist many different approaches to test the advantages of such a system. This paper proposes a concept to simulate and test different strategies for implementation variants. The controller is developed as a module for Bifrost, a simulation and demonstration software.

The key contributions of this paper are:

A. Introduce a flexible Energy Community Controller;
B. Present a methodology for using the simulation environment to enhance Energy Community control strategies;
C. Verify the approach based on an exemplary community settlement where local flexibility's (e.g., battery storage) optimize for self-sufficient load consumption;

The remainder of this paper is organized as follows. section II contains a review of related work, section III presents the Bifrost environment, and the methodology is described in section IV. The exemplary use case scenario and the results are both presented in section V. Finally, conclusions and an outlook can be found in section VI.

II. Related Work

The power generation mix in power grids in the EU has increased its share in volatile renewable energy sources like wind turbines and photovoltaic panels over the last decades [4]. While this increasing pervasion in electricity production from renewable resources is inarguably a step in the right direction to address high carbon emissions of conventional fossil-fueled power plants and meet the ever-increasing energy demand, the development comes with a new set of challenges for the power grid and its reliable operation.

Rapidly changing solar irradiance and wind conditions and their inaccurate forecasts can lead to imbalances between the power supply and demand. Additionally, the voltage variations caused by the volatile generation pose the risk of power quality issues by exceeding the standardized limits many electronic devices and power grid utilities rely on for normal operation [5] [6]. As more photovoltaic and wind power connects to the grid, these problems will become more prominent.

The idea of demand response (DR) is considered a viable part of the solution to keep up with the need for more

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renewable energy sources while also enabling flexibility on the power grid to handle their volatility and has been widely covered in the scientific literature [7] [8]. The term DR is not a single technique but encompasses multiple distinct methods of attuning energy demand on the end-user side to the production - i.e., in residential households, commercial and communal buildings, and industrial facilities.

The electrical devices available for controlling in a demand response scheme are, among others, residential and commercial refrigeration systems, building heating systems, batteries, and electric vehicles. One specific area of DR considers the volatility of renewable energy sources and devices available for control as flexibilities in the power grid. The aim is to allow renewable energy sources with high energy production variations, such as photovoltaic and wind energy, to be balanced by controllable appliances that can ramp, shift or curtail their power demand, thereby stabilizing the grid [8] [9] [10].

Simulations of power grids in conjunction with simulations for information and communication technology can enable faster and cheaper evaluation of a wide range of future smart grid and demand response technologies. Because of the inherent complexity and size of the systems studied, homogeneous simulation tools are prone to oversimplification of the problem domain or do not scale well to the required size. In contrast, co-simulation approaches, consisting of heterogeneous systems working together, suggest better results [11].

Recent studies on the collective control of multiple buildings' energy consumption have focused on model-predictive-control architectures for controllers [12], scheduling algorithms for energy flexibility dispatching [13] [14] and validation of photovoltaic simulation models [15]. Concering the prediction of residential demands or renewable energy production, there is a variety of time series forecasting methods available [16] from the simple ones such as Autoregression (AR), Moving Average (MA) merging into Autoregressive Integrated Moving Average (ARIMA) that is the most commonly used for a univariate time series with further extension for seasonality (SARIMA, SARIMAX). Vector Autoregression (VAR), Vector Autoregression Moving-Average (VARMA) and Vector Autoregression Moving-Average with Exogenous Regressors (VARMAX) are used for multivariate time series. Simple Exponential Smoothing (SES) and Holt Winter's Exponential Smoothing (HWES) rounds up the classical approaches [16]. Furthermore, extensive data availability allowed the wide spread of neural networks in general and Long Short Term Memory (LSTM) networks. And finally, due to the growing complexity of applications, hybrid approaches are becoming widely spread using multiple methods to improve the accuracy of predictions [17].

A common problem with demand response is the missing experience regarding the capabilities and the problems emerging from large scale applications. This lack of experience repeatedly results in the need for extensive assumptions in previous studies [8]. Assessing the viability of control strategies for flexibilities is costly in real-world field experiments because of the systems studied' size and complexity. Other problems

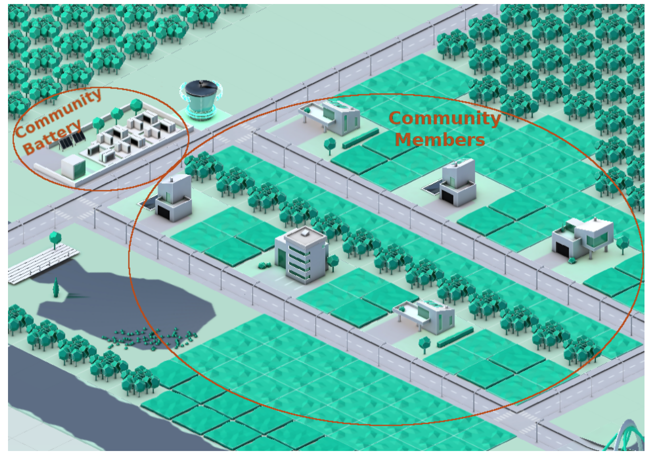

Fig. 1. Energy community settlement with six households and one community battery in Bifrost

in previous years were regulatory barriers that did not allow individuals to take part in coordinated control schemes. In the European Union, this is now becoming possible through the introduction of legal frameworks like the "Renewable Energy Community" and "Citizen Energy Community" [2] [3] [18]. Additionally, Jordehi et al. [19] identifies the need to attract more residential consumers to demand response programs. Creating tangible simulations that are more easily accessible for parties interested in joining energy communities could enable them to anticipate the benefits and reduce the inhibition level for wavering parties.

III. The Bifrost Environment

Core: Bifrost[1] is a simulation coupling platform with a web-based 3D interface for the construction and management of communities. External simulation modules can hook into the core simulation loop and fill the Bifrost data model with dynamic data. The core takes care of calling the modules in a deterministic order and with the desired subscription data and merging the values they provide into the data model. In this way, specialized domain models can be chained together to achieve the desired output at the end of each simulation loop. Bifrost is designed to run continuously in accelerated real-time: a simulation iteration takes one second in real-time and between one second and several hours in simulation time, dependent on the connected modules and the desired analysis scale. Figure 1 shows a typical settlement in Bifrost which serves as the base for the scenario in section V.

Modules: Bifrost uses several modules to provide the desired functionality. Apart from the core module, our environment includes a building model representing households, commercial buildings, community buildings and more. Figure 2 shows the building model with its different sub-modules. A more detailed description can be found in Section IV. Furthermore, a weather generator replays weather conditions for the desired date and location. To adjust the time frame for

[1] https://bifrost.siemens.com

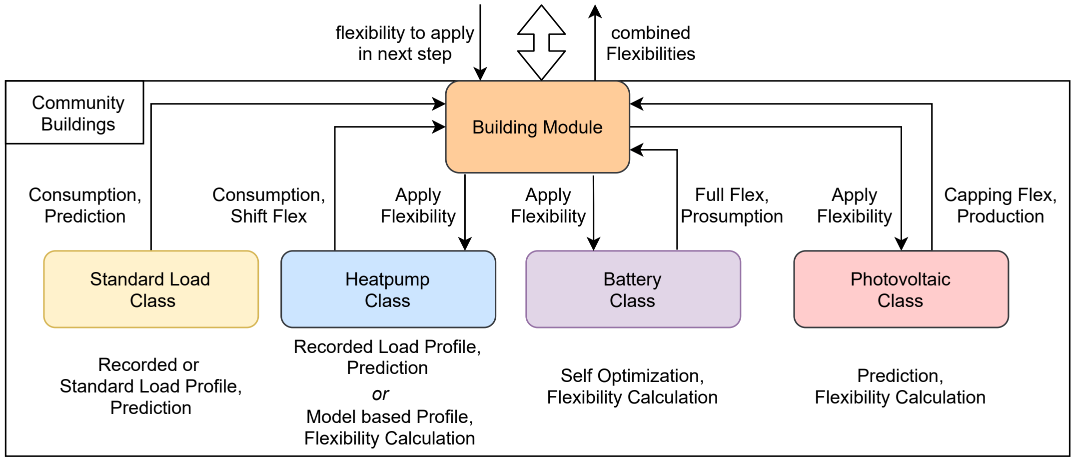

Fig. 2. Building Model functionality with data exchange to EC controller

simulation, it integrates a module called timetargeter, allowing jumping back and forth in time with adjustable time steps and more. A battery model serves the purpose of integrating community batteries. The model provides the option to select various types of batteries or configure them directly in the simulation environment. The model features options to integrate self-discharge, ageing and efficiency for the charging and discharging process. Moreover, it provides the option to provide DC power to electric cars or similar loads. To supply the community controller with information about the grid or other communities, a separate grid operator/higher-level controller module integrates this functionality.

IV. Energy Community Controller

The proposed energy community controller is the groundwork for testing future renewable and citizen energy communities integrating the EU directives [2] and [3]. It has the role of a managing instance to ensure the proper function of such communities. For achieving the highest possible benefit the underlying algorithms, strategies and data exchanges for a basic simulation concept are laid out in this section.

Figure 3 shows an overview of all the participants of the energy community, including the controller, member buildings, community batteries and the higher-level controller/grid operator. The chain of command is from left to right, meaning the higher-level controller may request flexibility from the community controller, who can reserve flexibilities according to the request. The community controller aggregates available flexibility from members, including buildings and community batteries and orders the members to apply certain flexibilities upon demand. This process should ensure reducing the grid load and, when necessary, support the grid. The buildings can provide different kinds of flexibilities depending on the installed systems—these range from heat pumps over photovoltaics (PV) to batteries. The community batteries provide flexibility for all members and are shared accordingly.

For simulating requests due to shortages in the grid or inter-community exchanges, another module simulates a grid operator/higher-level controller that negotiates flexibility with the community controller based upon the grid's status. The various grid status are based on the definition in [20]. These states determine which control scheme the controller uses. In the best case, the grid is in a green state where the community controller can act independently without interference from a higher entity. Suppose the grid state is influenced by low production/consumption, the state changes to yellow. In this state, the grid operator can signal the community controller to provide flexibility upon availability. If the state deteriorates even more and changes to the red state, the grid operator signals the EC controller to provide a specified amount of flexibility. In this state, the controller must provide energy as agreed upon, preventing the grid from greater difficulties. The community should get appropriate compensation for doing so.

A. Aggregating and Balancing of Flexibilities

The community controller handles the exchange of flexibilities. The exchange includes the distribution of energy, calculation and logging of the energy exchanges, and communication with a higher-level controller/grid operator to integrate the grid status into the calculation and distribution.

Flexibility types: This concept for an energy community controller simulation includes different flexibility types to cover as many cases as possible. There are three types in this framework: full flexibility, shift flexibility, and loss flexibility. Full flexibility describes units in the system that can provide their available energy without losing the ability to power devices like shutting down flexible loads or losing the chance to use the energy at all. On the other hand, shift flexibility provides short-term energy that has to be compensated for shortly afterwards. Loss flexibility is an energy that is not converted into electrical energy or electrical energy that is not consumed but cannot be consumed afterwards. Examples for these types of flexibility would be a battery for full flexibility being capable of providing energy when needed as long as the charging level is sufficient. For shift flexibility, a heat pump or electric car would be an example of delayable energy

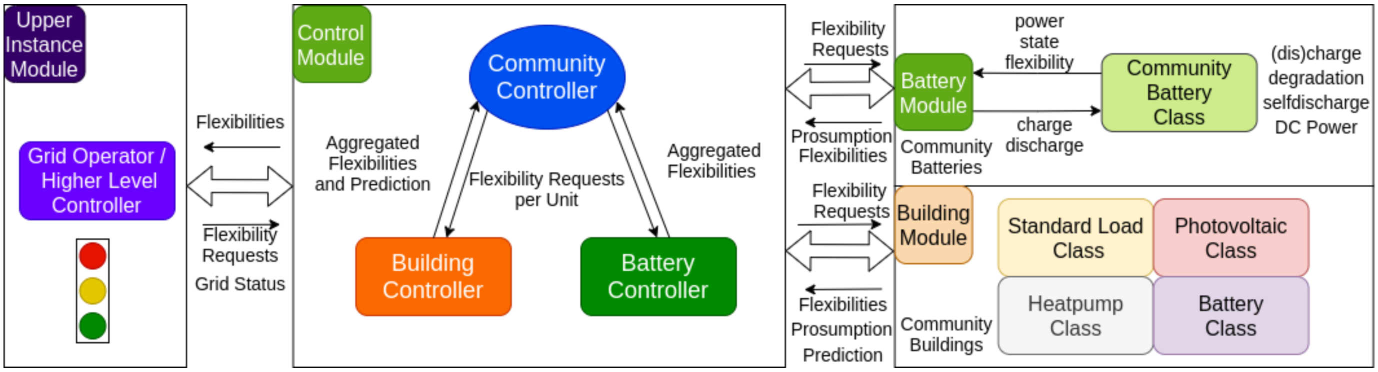

Fig. 3. Overview of the EC Controller scheme

consumption. For loss flexibility, an example would be a photovoltaics converting less radiation energy than available into electrical energy, therefore "loosing" potential energy. Figure 4 shows the community- and member demand with coloured arrows illustrating possible use of flexibilities and red and green blocks illustrating the energy consumption and production of the whole community with demand in black.

The EC controller collects all the flexibilities from the building and battery controller. The building and battery controller themselves again collect the flexibilities from the underlying building model and battery model. The building model provides the prediction for consumption and production as well. The community battery does not provide predictive values as the community solely controls its behaviour.

Scheme for a round of communication: the scheme for doing one step of community interaction is as follows. All the community members household controllers collect their current consumption, which corresponds to the last time frame's consumption or step. Furthermore, they collect the sole consumption of all the separate modules that are capable of providing flexibility. Afterwards, prediction takes place for the different loads: the standard household loads not separately tracked, the PV installation, and heat pumps and flexible loads. For the batteries, no predictions have to be made as they are fully controllable. Based on these single predictions, a prediction for the whole household consumption for the next step is transmitted to the community controller and ranges for different flexibility types. On the other hand, the battery controller also collects the previous consumption for all the member batteries. It calculates the flexibility for the batteries based upon the specifications of the batteries and the state of charge. The community controller then collects all the aggregated flexibilities and acts upon them. The grid can be supported if necessary. After determining the grid's state by communicating with the grid operator, it balances the members' loads. It starts with using the available capacity of the community batteries as a first approach. If necessary or desired, the amount of energy that cannot be distributed among the batteries is distributed to the entities which provide shift flexibility like heat pumps. These short time flexibilities should only be used if the grid requires it or if the long-term

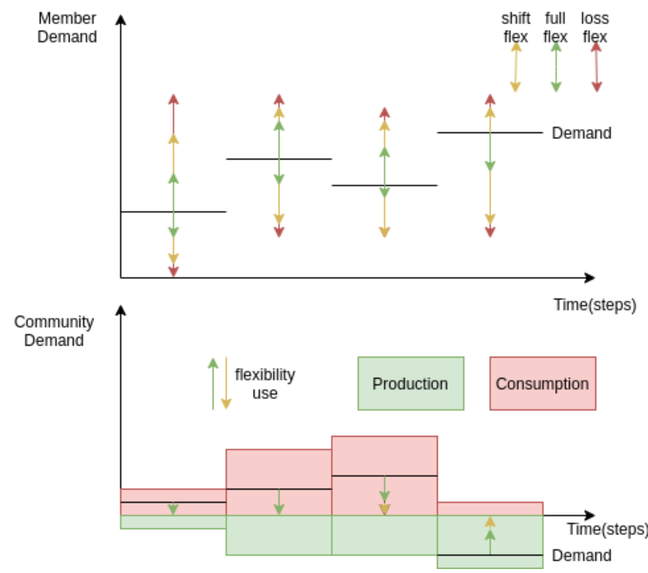

Fig. 4. Member and Community Demand with available flexibility and use

perspective allows such measures. As a last resort, the PV production can be reduced to prevent grid failures.

B. Community Balancing Mechanisms

For the prioritization of member flexibility, different mechanisms provide varying advantages. At the current state, two distinct mechanisms can be selected. The first approach uses flexibilities evenly from all the household, not considering which member provides more or less flexibility. In the case of some members not being able to provide the same amount of flexibility as others, the remaining flexibility is distributed among members capable of supplying a higher amount. The second approach uses a quota scheme where every provision of flexibility is recorded and used as a base for future distribution of flexibility. It leads to members providing more energy than others being able to get more energy later on. The first approach has its advantage in relying on more diverse sources of flexibility, whereas the second approach allows a fairer distribution of energy as members contributing more to the community to receive more from the community in exchange.

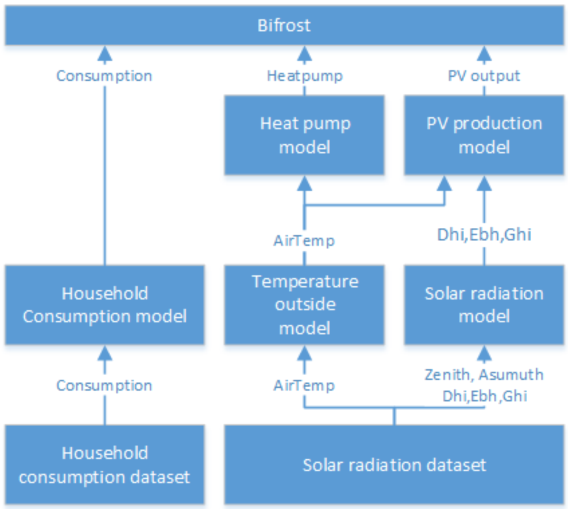

Fig. 5. Prediction models information flow

Regarding balancing the load for 24 hour prediction we want to use a linear programming method. The simplex algorithm [21] is a possible solution for such problems and we will use this algorithm to find an optimal solution.

C. Modeling demand for heating

The building model incorporates a class for heat pumps. At the current stage, its demand represents the normalized consumption for a heat pump of that type. The output power at a given hour of the day calculates with the outside temperature at that time. For the next stage, a model for thermal demand of the buildings similar to the one presented in [22] will be used, providing a building adapted demand for the heat pump.

D. Predicting local energy production and consumption

For the appropriate distribution of energy and flexibilities, it is necessary to predict future consumption and production. In a household, the standard loads, heating requirements, PV production and possible flexible loads should be predicted. A combination of neural networks and analytical models provide forecasting for Bifrost to operate where the neural networks predict household consumption, outdoor air temperature and solar radiation. The former is directly fed into the control environment, air temperature is fed into the model of heat pump, and solar radiation is used in the PV production model. All three models use LSTM neural networks with 125 neurons of the hidden layer combined with a dense output layer. The consumption model used for the standard load profile uses two previous observations as an input and a single output for prediction, the same way the air temperature model is structured. The solar radiation model uses five inputs: Azimuth, Zenith, diffuse-horizontal-, direct-normal-, and global-horizontal-irradiance (Dhi, Dni, Ghi), each with two previous observations and three outputs. The consumption dataset used for training consists of 32.000 measurements for 15-minute intervals, corresponding to roughly 11 months. Air and Solar base on a common data-set consisting of 470.000 observations in 15 min intervals ($\sim$13 years). Consumption and Solar datasets have a right-skewed distribution, with the majority of measurements having small changes and rare peaks, which challenge forecasting. However, the LSTM models managed to detect patterns and struggles in peak situations only. Contrary thereto, the air temperature is characterized by a normal distribution and shows minimal deviations from the expected values. These three models are used in the scenario where planning is performed only for the next 15 min interval. The other scenario is day-long planning, where the models' outputs are 96 values of 15 minutes interval using autoencoder models with LSTM. Figure 5 shows the prediction models with its necessary information flow.

V. Usage Scenarios and Results

This section presents a simple usage scenario for the controller in an energy community and preliminary results of the ongoing development. As mentioned in Section III, Figure 1 shows a Bifrost settlement with a community battery and six community members. Three of the households have a PV installation with 5 kW of peak power, each facing southwards. A community battery extends the settlement capable of supplying 11 kW of power with 100 kWh of capacity. The simulation starts at a specific point in time with fixed parameters for weather and environmental conditions and runs for seven straight days (simulation time) without an active controller. Afterwards, the simulation is repeated with the controller actively performing single step predictions and flexibilities balancing, including the battery.

Figure 6 shows the curves for the community's power consumption with and without the controller showing a change for the community's maximum and minimum power consumption. The power that was previously inserted into the grid is now consumed by the battery and afterwards used to compensate for the demand of the households. The controller has to predict the household demand and PV production precisely to request the right amount of flexibility from the battery as there are only 15-minute values available on the community controller side. The scenario uses 15-minute time-steps to verify the behaviour, showing minor inaccuracy in predicting the community's demand. The spikes remaining arise from the battery being empty after some time due to insufficient charging power from the PV installations.

This scenario shows the operation of the controller in its current state. The controller reduces the peak power drawn from the grid by 21.4 % and the power fed into the grid by 89.5 %. The energy drawn from the grid is reduced by 53 %, and the energy fed into the grid by 98.9 %. More complex predictions and models will be used for future work, and the number of available loads and flexibility providers will be increased. Concerning prediction, all three models were able to detect the training datasets' underlying patterns and showed varying degrees of deviation from the test datasets' actual values. The household consumption model struggled to predict the peak values accurately, but 89 % of the predictions were

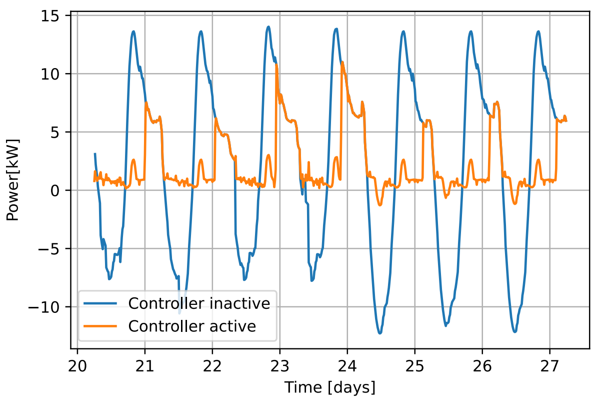

Fig. 6. Energy Community Power Consumption over several days

under 10 % deviation. The solar irradiation model showed similar results but managed to nicely detect peak values (only 3.5 % of Dhi predictions above 10 % deviation from the actual values, 6.7 % for Dni, and 1.6 % for Ghi). The air temperature model is most accurate with no deviation above 10 %.

VI. Outlook

Further work will be done regarding prediction accuracy and bridging Bifrost with a hardware-in-the-loop connection in real households for further data points in the system. Additional factors, such as economic feasibility, cost calculation, and impact of the energy controller towards the CO_2-footprint of the community's energy mix, will be added to the system. Regarding the controller, an implementation of the day-ahead prediction will follow. Furthermore the model predictive control needs to be finished and included to properly predict demands. Additionally the buildings heating demand module needs to be implemented to complete the heat pump. Due to the fact that the vast majority of changes in the consumption model are minimal with sudden peaks, anomaly detection methods would provide better results. The solar irradiation model might benefit from more input parameters to improve the performance, whereas the air temperature model may be substituted by naive forecasting since the changes between measurements are minimal and gradual.

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Disclaimer

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