Assessing Model Predictive Control for Energy Communities' Flexibilities

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ABSTRACT:
Renewable energy communities (REC) are legal entities defined by the European Clean Energy Package to own and share energy resources. A common goal of RECs is to have a high self-consumption. This work focuses on how self-consumption can be increased by means of intelligent control of flexibilities based on a use case featuring a community battery energy storage (CBES).

Many simulation studies for the control and optimization of distributed energy resources (DER) including community storage exist, focusing on various aspects, however, often neglecting important effects for a real implementation due to simplified assumptions:

(A) The control or optimization routine is run open loop. Thereby, the influence of prediction and modeling errors is ignored, so that the results obtained represent only an upper limit for the effectiveness.

(B) The availability of data is not considered appropriately which might render certain control approaches unpractical. In practice, this might be a limiting factor for forecasting methods and control methods in general. Especially, as RECs are of a distributed nature and the implementation of potentially costly data acquisition and information infrastructure could limit the economic rentability significantly.

We investigate a realistic use case, constructed based on the current Austrian legal definition of RECs. Here, recent smart meter data of the REC participants, as it is made available by the distribution system operator (DSO) for settlement purposes. We utilize this data for control. Our realistic simulation model consists of several residential loads, a community PV system, two private PV systems and a CBES which is controlled to boost the RECs self-consumption. The model was implemented within the MOSAIK co-simulation framework. Due to the enforced modularity of this framework, the controller is integrated into the simulation model in a closed loop manner, addressing limitation (A) of similar studies. In addition, the data exchange between the different actors, such as the grid operator and the REC operator, is modeled, which clearly addresses limitation (B).

A promising method for the control problem of the described REC is model predictive control (MPC) and its solution by means of mixed integer linear programming (MILP). To control the community storage system using MPC, an accurate prediction of the residual load is required. This forecast is created using a machine learning model (LSTM

model), which is pre-trained on synthetic load profiles to improve the prediction with limited data availability.
Results show that MPC can handle the model and prediction uncertainties generally well. Nevertheless, the consideration of forecasting and modelling uncertainties in the simulation shows that the achievable self-consumption rates can be significantly reduced. Utilizing simplified forecasting and considering modelling uncertainty reduces the self-consumption by up to 14.5% points in the use case considered. These losses can, however, be contained by accurate prediction methods. With the consideration of modelling uncertainties for the CBES model alone, we find that a discrepancy between real storage capacity and controller model capacity of 20% reduces the self-consumption by 3.9% points. As the CBES can be considered a comparably "easy to model" component, this highlights the need for closed loop simulation in the controller development for RECs.

1. INTRODUCTION

Under the Clean Energy for All Europeans Package (CEP) (European Commission, 2019), several legislative actions have been taken, to move away from fossil fuels and to achieve the Paris Climate Agreement. Within this package, energy communities are defined in two variants once in the Renewable Energy Directive (RED) (*EU 2018/2001*, 2022) and in the Electricity Market Directive (EMD) (*EU 2019/944*, 2022).
A Renewable Energy Community (REC), as it is considered here, is defined by the Renewable Energy Directive as *"[…] a legal entity: (a) which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity; (b) the shareholders or members of which are natural persons, SMEs or local authorities, including municipalities; (c) the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits;"* (*EU 2018/2001*, 2022). The law refers to SME which means small and medium-sized enterprises.
The European directives have been transposed into national Austrian law with a particular focus on the role of the distribution system operator (DSO) and its interactions with the REC (Fina and Fechner, 2021). This allows for the consideration of a realistic scenario under the Austrian legal framework.

Self-consumption of the energy community's generation is found to be the main contributor for the economic rentability (Van Der Stelt et al., 2018). It can be enhanced by efficient control of flexible distributed energy resources (DER) such as CBESs.

Recent works regarding the control of battery energy storages in the context of RECs have considered several peculiarities.
(Pasqui et al., 2023) investigates how the control of individual batteries affects community self-consumption and finds that standard management of batteries has a negative effect on self-consumption. The authors present a new approach to control battery

storage that significantly increases community self-consumption and only slightly reduces individual self-consumption. The approach is benchmarked against a scenario with perfect prediction and optimized loads using mixed integer linear programming.
(Van Der Stelt et al., 2018) examines the economic rentability of household and community storage systems and smart household appliances using MILP. They find that the rentability of storage systems depends heavily on the investment costs per capacity but is currently uneconomical. Results show that the self-consumption of PV generation is the largest contributor to the savings obtained when using ESS.
(Walker and Kwon, 2021) create a mathematical optimization problem for the optimal operation to compare individual and community storage systems. They find that community storage systems are more advantageous, in terms of both, costs and utilization.
(Berg et al., 2023) investigate how a community storage system affects the distribution grid. It is shown that battery storages can violate the voltage limits of the distribution grid.
(Korjani et al., 2021) implement an algorithm based on a genetic optimization method that can be used both as a planning tool and as a controller for a battery storage system acting as a virtual power plant. They integrate a prediction and the system capable of real-time operation.
(Houben et al., 2023) develop a forecasting method and MPC framework and apply it to a testbed of a renewable energy community in Austria. The objective is to reduce the operational costs and CO^2 emissions under several price tariffs. The MPC outcomes are benchmarked against a rule-based control strategy and the impact of forecast errors and electric battery capacity on the savings is examined. Their findings show that forecasting errors can be a great threat to the savings achieved.
(Nagpal et al., 2022) present a hierarchical management framework for energy communities including a CBES utilizing MPC. Individual participants make self-driven, cost optimal decisions which are then coordinated to increase the community's self-consumption and self-sufficiency.
(Tostado-Véliz et al., 2022) propose a two-stage optimization framework to first optimize the energy exchange between prosumers, and second, plan the operation of various collective distributed energy resources and the energy exchange with the grid. A novel approach with stochastic intervals has been developed to account for uncertainties related to prosumer demand, renewable energy generation, EV behavior and energy prices.
(Talluri et al., 2021) propose a battery energy storage control strategy with three modules: first, machine learning-based forecasting, second, a MILP based optimization for minimal REC operating costs and self-consumption considering the electricity price, variable feed-in tariffs for PV generators, battery storage cost and third, a decision tree algorithm that works at minute intervals for real-time control. They build a use case of an Italian small-scale REC.
(Manso-Burgos et al., 2022) develop a method to optimize local energy communities with a battery energy storage system. The authors investigate different capacities, ownership options and different sharing strategies.

(Aittahar et al., 2023) formulate the control of an energy community's flexibilities as an optimal control problem. The generated electricity is thereby redistributed to its community member using repartition keys. The formulation enables a joint optimization of the controllable assets and electricity redistribution.
(Frieß et al., 2023) introduce a MILP framework to optimize the energy flows of an energy community with various flexible assets. It is applied in an iterative manner as MPC. The presented framework can be used to generate realistic performance measures of specific community configurations and to evaluate strategic investment decisions.

In the articles presented, we find a general lack of applicability of the control approaches. Even though uncertainty is often mentioned, its influence is mostly not considered. Further, most of the articles mentioned do not apply the optimization problem in a closed-loop manner, such that it could be applied to a real system. Amongst those that apply closed-loop simulation, none have investigated the influence of modeling uncertainty on the control outcome systematically. Articles using closed loop and forecasting, usually apply simplified prediction methods such as persistence forecast. The more sophisticated machine learning approaches for forecasting rely on historic data measurements that might not always be available.

To address these limitations, we present a framework, that allows to assess the control algorithms effectiveness in RECs more practically. We consider the uncertainties from a practical perspective by implementing different models for optimization and simulation in a closed loop as well as by using real forecasting methods.
Due to the implementation of our framework with the co-simulation framework MOSAIK, the availability and origin of data used for prediction and control during real-time operation are made obvious. To our knowledge, data origin/availability is not regarded or discussed in the literature. However, we consider the data availability and flows as a key factor when controlling flexibilities such as battery storages in RECs as the system is of a distributed nature. We assume, that costly data acquisition and information infrastructure can be a critical financial aspect for energy communities.
The explicit consideration of data availability highlights the fact of limited historical data availability for an accurate machine learning prediction on the commissioning of an REC. To overcome this issue, we utilize a novel transfer learning approach, limiting the required historical data to the bare minimum.

We present a use case with household loads, PV generation and a CBES as flexibility, utilizing a model predictive controller which is solved by means of MILP.

Wrapped up, our contributions are the following:

- Consideration of modelling uncertainties between controller model and simulation model running in closed loop.
- Consideration of prediction uncertainties thorough two prediction algorithms and a perfect prediction scenario as a benchmark.
- Clear statement and visualization of data flow and availability to the CBES controller.

2. METHODS

The practical analysis of the controller design effectiveness is achieved with a simulation model based on realistic assumptions concerning the data availability. First, an overview of the modeled REC including the considered data flow is given, then the models and controller are explained in detail.

A general scheme of the framework is depicted in Figure 1. Here, household loads, PV systems, and flexibilities are considered. The latter two can either be connected to their smart meter individually or in combination with a household load. This showcases different possibilities for connecting flexibilities and generation to the grid and highlights the impact on data availability.

Data from the smart meters is collected by the distribution system operator (DSO). For accounting purposes, this data is provided to the REC. Thereby, the measured power profiles of the previous day are provided daily (Österreichische Koordinationsstelle für Energiegemeinschaften, 2024). We assume, that this data can be used for control.

Our use case features 74 household loads and three PV systems. Of those, one is a south facing PV system connected to an individual smart meter, fully feeding into the grid. Additionally, two PV systems, facing east and west, are connected to households behind the meter, acting as surplus feeders. As flexibility, we utilize a CBES grid-connected via a separate metering point. It is controlled by MPC controller on site. The modeling and parameters of the models will be stated in the respective Sections 2.1-2.8. Due to the inability to distinguish between load and PV generation for the surplus feeders (PV systems connected behind the meter), a further connection from the PV systems to the controller is established. This data from the PV systems includes power measurements and weather information (temperature). We assume that these measurements are most likely available at modern inverters and therefore no additional, potentially costly, data acquisition infrastructure is needed.
A distinction between load and generation is needed here for the control algorithm which utilizes this data for demand and generation forecasting which will be explained in detail in Section 2.8. acquisition

Connections between the components of the model and the distinction between physical connections, real-time data, and the lagged forwarding of information by the DSO can also be seen in Figure 1.

The model is implemented in *Python*, utilizing the framework *MOSAIK* (Ofenloch et al., 2022) which is built for smart grid analysis. The framework enables the use of existing simulation models, thus limiting sources of error, and also allows for the integration of hardware in the loop. It furthermore visualizes the necessary connection between the components and simplifies the generation of scenarios.

The simulation is set up with a time resolution of one hour. The models will be explained in the following.

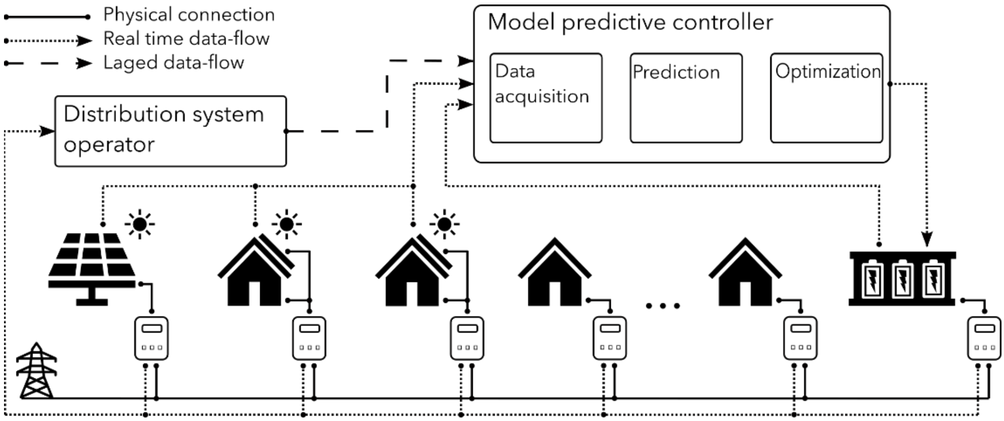

Figure 1: Scheme of the energy community framework and model.

2.1 HOUSEHOLD MODELS

The household models are based on real household load data for 74 real households from 2010 (Tjaden et al., 2024). Metadata for the households is not provided, i.e., there is no further information about the location, number of residents, and other details of the households available. However, those profiles are described to be representative of single-family homes in Germany due to a validation against standard load profiles (Tjaden et al., 2024).

For use in the simulation, the 15-minute data is down-sampled to hourly resolution. During preprocessing, the data for the months November and December are prepended to the beginning of the dataset to enable the training of the forecasting algorithms (as will be elaborated later) and still allow for a yearly simulation.

2.2 PV MODELS

PV models are created using the *Python* library *pvlib* (Holmgren et al., 2024; Jensen et al., 2023). In accordance with the household models, data was used from the year 2010. The location of all PV systems is latitude=47.406313° longitude=9.744657°. Additional parameters for the PV system model, passed to *pvlib* are: The chosen technology as crystSi, the mounting place as building integrated, the losses of the overall PV system as 15%, and the option to calculate the optimal surface tilt as enabled. The parameters that are different for all three PV systems are summarized in Table 1.

Table 1: PV model parameter.

	Surface Azimuth (°)	Peak power (kW)
PV Model 0	180 (south facing)	125.0
PV Model 1	90 (east facing)	62.5
PV Model 2	270 (west facing)	62.5

2.3 SMART METER

The smart meter is modeled as a simple instance, summing up all collected loads behind the meter and forwarding them to the grid model and the DSO assuming no time delay. As a significant time delay is assumed from the DSO to the REC, the time delay from the smart meters to the DSO can be neglected.

2.4 GRID

The grid sums up all the connected entities' power flows, to calculate the power of the REC drawn from or fed into the grid.

2.5 COMMUNITY BATTERY ENERGY STORAGE

For the CBES, three variants have been modeled, with varying parameters and different degrees of detail, to investigate the influence of modeling uncertainty of the controller on the overall control results.

- The first model is a simple model considering maximum capacity and efficiencies for charging and discharging, using identical parameters for the MPC controller.
- The second model equals the first model except for the maximum capacity being set to 80% of the original capacity to imitate degradation.
- The third model is based on the second model but includes an additional self-discharge rate. The self-discharge losses are proportional to the energy currently stored.

Parameters of the models are summarized in Table 2.

Table 2: CBES model parameter.

	Capacity (kWh)	Efficiency, charging/discharging (%)	Maximum power charging/discharging (kW)	Self-discharge rate (1/s)
CBES Model 0	250	95	250	0
CBES Model 1	200	95	250	0
CBES Model 2	200	95	250	$2.0*10^{-8}$

2.6 MODEL PREDICTIVE CONTROLLER

The controller of the CBES is implemented as MPC and consists of 3 main structural parts, refer to Figure 1. First, the data acquisition and handling, second the prediction algorithm, providing forecasts of the residual load of the REC which is in turn needed for the third part, namely the optimization. Data acquisition and forecasting will be explained in Sections 2.7 and 2.8, respectively. Hereafter, the optimization problem will be elaborated on.

In MPC, the control problem is formulated as an optimization problem which is solved for a receding horizon. Only the first entry of the control signal horizon, which is the solution of the optimization, is applied to the real system. Then, the optimization is run again (after one hour) with updated inputs from the system.

The optimization problem to control the power of the CBES at hand can be formalized as a MILP which contains a model of the CBES as part of the constraints. The overall objective is to maximize the REC's self-consumption, following

$$selfconsumption = \frac{E_{\mathrm{PV}} - E_{\mathrm{grid}}^{-}}{E_{\mathrm{PV}}} \cdot 100,$$

with E_{PV} and E_{grid}^{-} being the total generation and the total feed in from the REC, respectively. Reformulating this to a linear objective means minimizing feed in $E_{\mathrm{grid}}^{-}$by controlling the CBES power (as the generation cannot be influenced here).
However, targeting minimal energy export leads to the effect of the storage efficiencies being misused to waste energy, as will be shown in the results section. Therefore, the self-sufficiency, as the ratio of the consumption being covered by the self-produced energy, is used. It is calculated as

$$selfsufficiency = \frac{E_{\mathrm{load}} - E_{\mathrm{grid}}^{+}}{E_{\mathrm{load}}} \cdot 100,$$

where E_{load} and E_{grid}^{+} refer to the total consumption of the REC and the total energy drawn from the grid, respectively. As the consumption cannot be controlled, only the imported energy from the grid can be used as a linear objective. The optimization problem can therefore be formulated as follows:

$$\min_{P_{\mathrm{CBES}}^{+/-}} \sum_{t \in \mathcal{T}} P_{\mathrm{grid},t}^{+}$$

$$s.t. \forall t \in \mathcal{T}:$$

$$P_{\mathrm{res},t} + P_{\mathrm{CBES},t}^{+} - P_{\mathrm{CBES},t}^{-} - P_{\mathrm{grid},t}^{-} + P_{\mathrm{grid},t}^{+} = 0$$

$$E_{\mathrm{CBES},t+1} = E_{CBES,t} + \left(\eta_{BES}^{-} P_{\mathrm{CBES},t}^{-} - \frac{1}{\eta_{BES}^{+}} P_{\mathrm{CBES},t}^{+} \right) \Delta t$$

$$\underline{E_{\mathrm{CBES},t}} \leq E_{\mathrm{CBES},t} \leq \overline{E_{\mathrm{CBES},t}}$$

$$P_{\mathrm{CBES},t}^{-} \leq \overline{P_{\mathrm{CBES},t}}\, b_{\mathrm{CBES},t}^{-}$$

$$P_{\mathrm{CBES},t}^{+} \leq \underline{P_{\mathrm{CBES},t}}\, b_{\mathrm{CBES},t}^{+}$$

$$b_{\mathrm{CBES},t}^{+} + b_{\mathrm{CBES},t}^{-} \leq 1$$

$$b_{\mathrm{CBES},t}^{+}, b_{\mathrm{CBES},t}^{-} \in \{0, 1\}$$

$$P_{\mathrm{CBES},t}^{+}, P_{\mathrm{CBES},t}^{-}, P_{\mathrm{grid},t}^{-}, P_{\mathrm{grid},t}^{+}, E_{\mathrm{CBES},t} \in \mathbb{R}_0^{+}$$

Here, the powers for charging and discharging the CBES are denoted as $P_{\mathrm{CBES},t}^{-}$and $P_{\mathrm{CBES},t}^{+}$ respectively, where the superscripts "+" and "-" indicate positive and negative as seen from the virtual point of the grid connection of the REC. The variables are defined over a future time horizon $\mathcal{T}$ with time index t, which will be elaborated on later. $\overline{P_{\mathrm{CBES},t}}$ denotes the upper limit of the charging power and $\underline{P_{\mathrm{CBES},t}}$ the upper limit for the discharging power. To avoid charging and discharging at the same time, Boolean variables $b_{\mathrm{CBES},t}^{-}$ and $b_{\mathrm{CBES},t}^{+}$ are introduced, acting on the upper and lower limits of the charging power. Similarly, $P_{\mathrm{grid},t}^{-}$ and $P_{\mathrm{grid},t}^{+}$ denotes power fed into and drawn from the grid, respectively. $E_{CBES,t}$ denotes the energy content of the storage with its lower and upper limits $\underline{E_{\mathrm{CBES},t}}$ and $\overline{E_{\mathrm{CBES},t}}$. The forecasted values of the residual load (sum of PV generation and household loads) are denoted as $P_{\mathrm{res},t}$.

The optimization is run over the future time horizon $\mathcal{T} = \{-1,0,1, \ldots, t_n - 1, t_n\}$ starting at time $t = -1$. This is due to the significant runtime of the optimization. It is assumed that the control output can only be set in the next time step, so delayed by one hour. This means, that the first time-step of the optimization problem contains the control power output of the previous controller run and the current measurement of the CBES energy content. This is empathized in Figure 2.

Initial conditions of the real system are therefore set for the optimization problem as follows:

$$P_{\mathrm{BES},t=-1}^{+} = -P_0 \; if \; P_0 < 0, else \; 0$$

$$P^{-}_{\mathrm{BES},t=-1} = \quad P_0 \; if \; P_0 > 0, else \; 0$$

$$E_{\mathrm{BES},t=-1} = E_0$$

Where P_0 ($\in \mathbb{R}$) as exogenous input stems from the previous time steps optimization output and E_0 ($\in \mathbb{R}$) is the measured energy content of the CBES of the previous point in time.

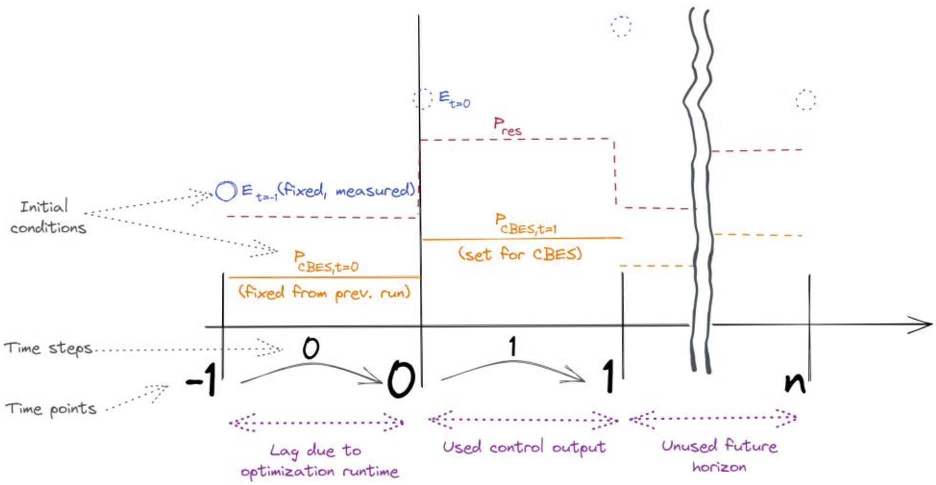

Figure 2: Visualization of the optimization time horizon.

The optimization problem is formulated in *Python* using the *pyomo* modelling language (Bynum et al., 2021) with the *glpk* solver.

The parameters of the controller model can be seen in Table 3.

Table 3: Parameters for the CBES controller model

	Capacity (kWh)	Efficiency, charging / discharging (%)	Maximum power charging / discharging (kW)
CBES Controller Model	250	95	250

2.7 DATA ACQUISITION

The data acquisition module manages the different data origins and the recording to provide inputs for the forecasting module.

According to Figure 1 and as explained previously, the controller receives three inputs, namely:

- the node data of all participants via the DSO, received daily on the following day at noon;
- the PV generation and weather data from the PV modules;

- the measurements from the CBES, namely state of charge and the actual power drawn or fed in.

As will be explained in detail in Section 2.8, the prediction algorithm needs to retrieve the true historic residual load. Therefore, the data inputs need to be preprocessed. First, the sum of all node powers of the community, as received form the DSO, entails the power of its flexible sources(CBES), the latter needs to be subtracted from the total power during preprocessing to get the residual load. In the case study considered, where the CBES is connected to a smart meter individually, this could be avoided as the power is available individually in the REC data form the DSO. However, to represent a more generic situation, where the storage could be connected behind the meter, this step is included.

Second, the LSTM forecasting model needs separate inputs for load and generation. However, as the PV generation and household loads cannot be distinguished in the node power data from the DSO for the surplus feeders, it needs to be recalculated. Therefore, the recorded power data from the PV systems is subtracted from the total REC power profile to obtain both, total PV generation and total household loads individually. These individual load and production data is then passed to the forecasting algorithm.

2.8 FORECAST

The aim of the forecasting algorithms is to generate an hourly prediction of the residual load of the REC being the difference of the total PV generation and the total load of the households. The prediction needs to be generated based on the available data from the data acquisition module and is later passed to the optimization module. The presented use case utilizes a future horizon of 24 hours which is updated every time the optimization is run once every hour.

The prediction is generated in one of the following three ways, providing different scenarios analyzed in the results section:

- A perfect prediction. This variant serves as a base scenario for comparison purposes.
- A long-short-term memory (LSTM) neural network load prediction combined with perfect PV prediction, which is the most sophisticated forecasting method here, implementing a novel transfer learning approach with an LSTM model which will be elaborated on in detail in the following. The PV generation is separated here, based on the assumption that under real circumstances, accurate weather forecasts can be used. As weather forecasts are not available ex-post for simulation purposes, a perfect prediction for PV is used.
- A persistence prediction which uses the load of the last week as a prediction (shifted 7 days, it is made available through the DSO) and the PV generation data from the last day (shifted 24 hours).

The LSTM model is published separately in (Moosbrugger et al., 2024) and will only be elaborated on shortly here. The model uses the load power from 7, 14, and 21 days ago and the weather data from the PV systems (temperature) as inputs. It further utilizes date and time features (day-of-week, time, day-of-year). The model is trained every 7 days and predictions are made hourly.

This novel prediction concept addresses the issue of limited data availability on the commissioning of an REC. The general principle is that the machine learning model is pre-trained on synthetic load profiles, as provided for clearing and settlement purposes for various electricity consumers from the clearing and settlement agent such as the (APCS Power Clearing and Settlement AG, 2024) in Austria. Then, this model is fine-tuned with real recorded data from the REC for the prediction. The general scheme of the forecasting model can be seen in Figure 3

In detail, the procedure for forecasting is as follows: Initially a LSTM model is trained with synthetic load data, in our use case with load data from (APCS Power Clearing and Settlement AG, 2024) from the year 2010. The model requires weather data as an input. However, as there is no weather data available for this synthetic load profiles, these input features are set to zero during the pretraining phase. During the runtime of the energy community, a new model is created every week, by first loading, the parameters (LSTM weights) of the pretrained model and secondly by finetuning the new model with a growing dataset recorded from the community (see Figure 3 for reference).

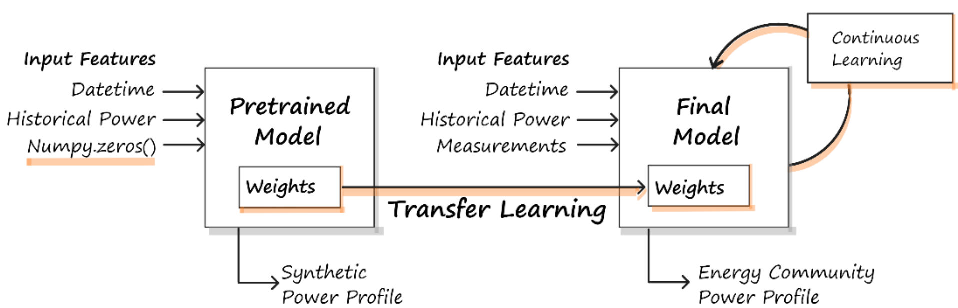

Figure 3: Basic principle of the LSTM load forecasting method. Reprinted from (Moosbrugger et al., 2024).

This continuous learning process fosters the development of a model that progressively enhances its generalization abilities. As shown in (Moosbrugger et al., 2024), this approach significantly outperforms the traditional approach without transfer learning. This allows to start making predictions with acceptable errors with as little as 2 months of historical load data after commissioning the REC. In addition to the reduction in prediction error, the whole training process gets more stable, i.e., the training loss converges faster and more repeatable.

For analysis purposes in this work, the model is finetuned using exactly two months at every weekly update. This fixed history length keeps the prediction error more constant over the simulation duration of one year and, therefore, allows for a fair analysis of the effects of the seasonality independent of the changing prediction error.

An example of the prediction of the load can be seen in Figure 4.

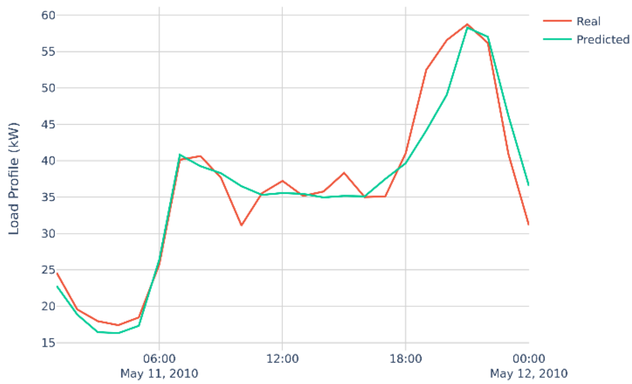

Figure 4: Example load prediction of the LSTM model.

3. RESULTS OF THE CASE STUDY

Nine simulation scenarios have been run as a combination considering three forecasting algorithms and three CBES models, where the latter has been controlled with the objective of self-sufficiency.

Exemplary simulation outputs for one scenario can be seen in Figure 5. As expected, the CBES is charged at times of high PV generation and discharged when the load surpasses the generation. It can be seen that the CBES is able to buffer almost all excess PV generation in winter but is not able to achieve this in summer and the transitional season. This can also be seen in Figure 6, where the self-consumption of all scenarios approaches 100% in the winter months but significantly decreases towards the summer season. The contrary can be seen for the self-sufficiency, which is around 20% in the winter season and increases to over 80% in the summer season for all scenarios. The influence of the reduced prediction accuracy with persistence forecasting on the self-consumption is greater in summer. The opposite is true for self-sufficiency, which is influenced stronger by the reduced prediction accuracy in winter and transition season.

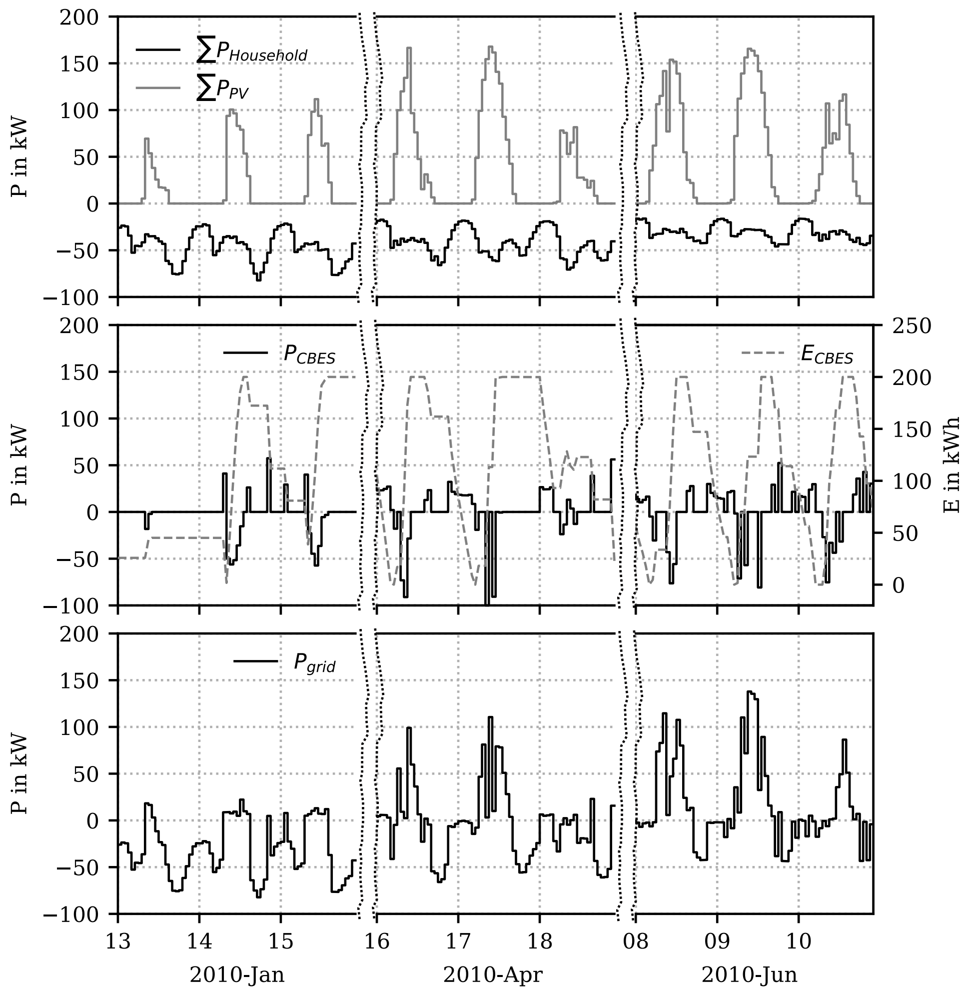

Figure 5: Exemplary power and energy outputs of the simulation for winter, summer, and transitional season for scenario with CBES model "reduced max. capacity, self-discharge" and prediction "LSTM load, perfect PV".

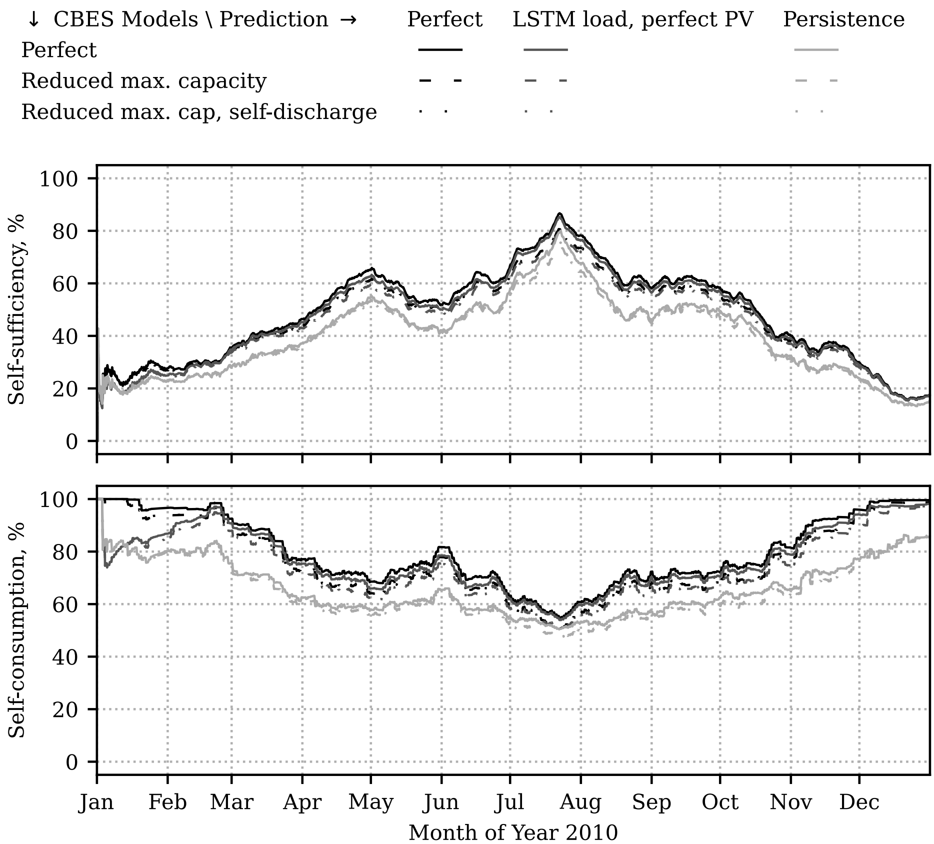

Figure 6: Annual development of self-consumption and self-sufficiency of the simulated scenarios calculated for the past 30 days as a running window.

The numerical results for the scenarios can be seen in Table 4 and

Table 5. Self-consumption rates for all scenarios are displayed in Table 4 and self-sufficiency-rates in
Table 5. As can be seen, the achievable self-consumption rates can be significantly reduced through forecasting and modeling errors. Utilizing the simplified persistence forecasting reduces the self-consumption by 12.6% points compared to the perfect prediction case, while the LSTM combined with perfect PV prediction only subtracts 2.3% points from the self-consumption. Both results assume perfect model knowledge.
The analysis of modeling uncertainties for the CBES model shows, that a reduced capacity scenario reduces the self-consumption by 3.9% points for the perfect prediction scenario. Self-discharge does not significantly influence the uncertainty. Compared to the perfect scenario, the scenario with persistence forecast and the CBES model with reduced max. capacity and self-discharge shows a decline of 14.6% points.

Table 4: Self-consumption over one year of the simulation scenarios in %.

Prediction / Storage model	Perfect	LSTM load, perfect PV	Persistence
Perfect	74.9	72.6	62.3
Reduced max. capacity	71.0	69.1	60.3
Reduced max. capacity, self-discharge	71.0	69.0	60.4

Table 5: Self-sufficiency over one year of the simulation scenarios in %.

Prediction / Storage model	Perfect	LSTM load, perfect PV	Persistence
Perfect	45.9	44.4	37.9
Reduced max. capacity	43.6	42.4	36.9
Reduced max. capacity, self-discharge	43.6	42.4	36.9

For comparison, the root mean squared error (RMSE) between the CBES controller model and the simulation model, calculated over the total duration of one year is given in Table 6. As can be expected, the accuracy of the model decreases with the reduced max. capacity. The additional consideration of self-discharge in the storage model leads to considerably smaller or no deviations in the RMSE for the scenarios as can be concluded from the results in column three of Table 6.

Table 6: RMSE between the power output of the controller model and the CBES simulation model over the complete year for all scenarios in W.

Prediction / Storage model	Perfect	LSTM load, perfect PV	Persistence
Perfect	0	0	0
Reduced max. capacity	7568.1	7371.4	7474.3
Reduced max. capacity, self-discharge	7552.3	7371.6	7424.6

Further results have been generated with self-consumption as the objective for control. Exemplary simulation outputs thereof can be seen in Figure 7. It clearly shows that the controller leads to high grid feed-in peaks during noon caused by the optimization problem misusing the efficiencies to reduce the total energy grid feed-in.

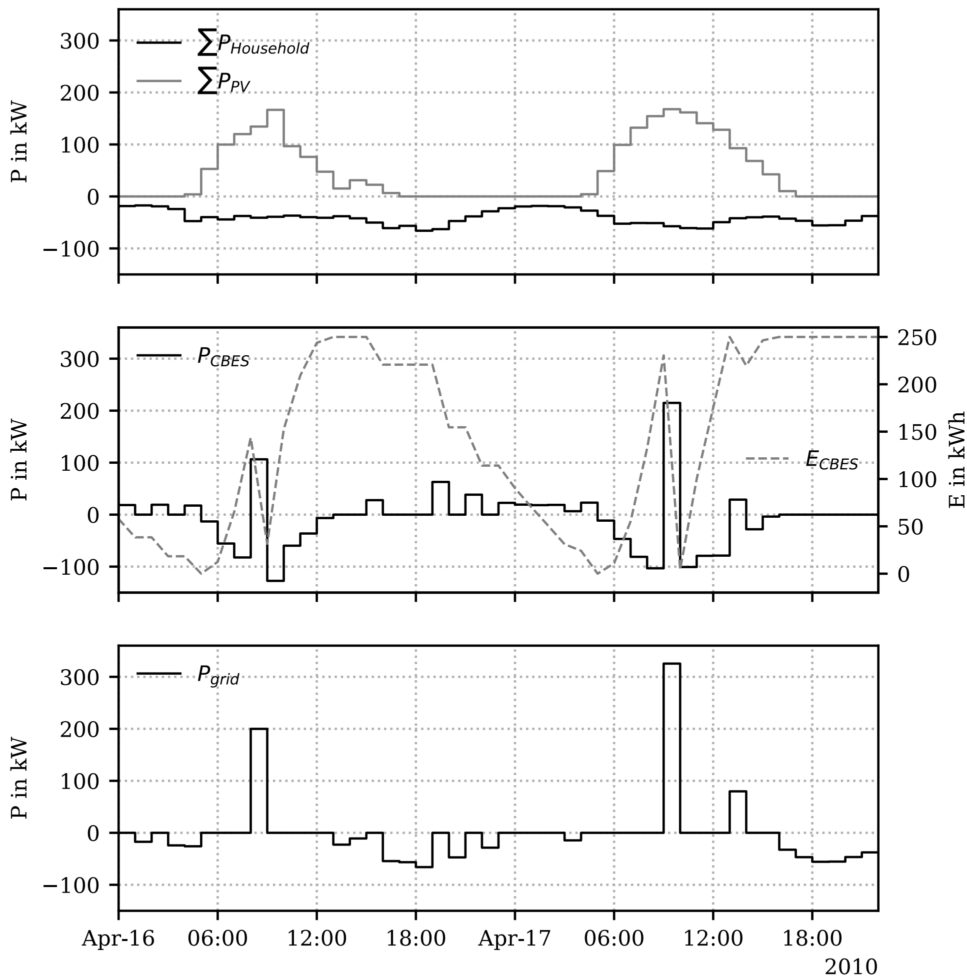

Figure 7: Exemplary simulation output, demonstrating the "waste of energy" when using self-consumption in the strict sense as an objective. Results are displayed for the scenario considering a perfect CBES model and perfect prediction.

4. DISCUSSION AND LIMITATIONS

Even though obvious, the exemplary model outputs of Figure 7 demonstrate nicely that self-sufficiency as an objective in the strict sense, grid-feed in being minimized, leads to undesirable results. The optimization therefore utilizes the efficiencies of the storage to dissipate electrical energy. This opens the general question of a REC's objective. Here, self-consumption (and self-sufficiency, leading to logically similar results) is used, as it is a simple metric, which has been shown to improve economic figures (Van Der Stelt et al., 2018). Centralized optimization targeting economic figures for an REC in the Austrian legal implementation might be difficult to achieve, as they require knowledge of the individual electricity tariffs of the participants.

Concerning modeling and prediction uncertainty, it can be seen, that prediction influences the results more significantly than the modeling errors. The implementation of self-discharge even shows no significant influence on self-consumption and self-sufficiency for all prediction methods at all. The significance of these results is however limited to the simplified use case considered. How control algorithms cope with these errors in reality (or with more realistic models) therefore remains a topic for future research as well as the consideration of other, "more complex to model" flexible energy resources like electric vehicles or heat pumps.

The seasonal changes of self-sufficiency and self-consumption over the year and the varying influence of the prediction uncertainty demonstrate the need for yearly simulations or at least the consideration of characteristic weeks or days, to assess control algorithms effectiveness.

The presented prediction algorithm for the load of the households can deal with the limited data availability upon commissioning of the REC well as can be seen in the results. It however remains unclear, how a realistic PV forecast influences these results. Difficulties arise from the fact, that historic weather forecasts are not as easily available ex-post as real predictions, where several online services exist.

A further question for future research is how the prediction algorithm deals with less and potentially changing numbers of households or loads, as it is expected that aggregation effects simplify the prediction for the use case considered.

A limiting factor for the significance of the results is the setup of the REC simulation model and the associated parameters. As there exists (to the authors knowledge) no arche-typical REC model, assumptions concerning the setup and the parameters had to be made. This additionally limits the comparability between different algorithms presented in the literature.

Further, the amount of data interfaces that need to be implemented between components and controllers need to be stressed. Data availability of the loads and generation could require the implementation of potentially costly data acquisition and IT infrastructure if not considered correctly. Figure 1 highlights the necessary connections between the components. Considering every single variable's availability at a certain place or component is enforced by the co-simulation framework setup and demonstrates its usefulness when considering more practical scenarios.

CONCLUSIONS

This simulation study of a virtual energy community with a community battery energy storage shows that model predictive control can handle both, model uncertainties and forecasting errors generally well proving its suitability for the application.

It is shown that the prediction error influences the achieved self-sufficiency and self-consumption more than the modeling errors, hinting at the importance of accurate predictions. Nevertheless, the influence of modeling errors is significant and might be even higher for "more complex to model" flexible energy resources like electric vehicles or heat pumps, which opens avenues for future research.

Finally, it can be stressed, how the use of a co-simulation framework highlights the necessary dataflows and interfaces, which might have been not considered otherwise. The framework furthermore simplifies the implementation of closed-loop control simulation and allows for a more realistic estimation of energy communities' control methods benefits.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the financial support from the Austrian Research Promotion Agency FFG for the Hub4FlECs project (COIN FFG 898053).

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