Co-simulation framework for calculating balancing energy needs of a microgrid with renewable energy penetration

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Summary
This paper introduces a unique simulation framework for testing and validating multiple operation issues of grid connected microgrids. The framework is widely adjustable and enables various control actions, for example, load shedding, demand response, power curtailment, and integration of battery energy storage systems (BESS). The microgrid operation framework runs several algorithms, providing data for the optimization of the actors at different time scales. In the first part of the paper, the framework, three predictor algorithms, and the network topology used for the tests are presented in detail. Balancing power requirements of microgrids are dominantly determined by uncertainties of intermittent renewable energy-based generation and changes in consumption. Beyond the environment development, the aim of the present research is to quantify the temporal change of balancing needs between certain confidence intervals. Accordingly, in the second part of the paper, possible approaches to determine the balancing power needs are presented, including the stochastic approach of the new System Operation Guideline (SO GL). The last part of the paper presents error characteristics of the predictor algorithms and balancing power needs are calculated in the context of the European balancing market terminology. Daily and seasonal temporality of errors is examined. The authors recognized that in transition to a more flexible distribution grid operation, the importance of possible microgrid market value propositions is increasingly appreciated. Future research perspectives include physical demonstration and validation of possible ancillary service strategy planning for microgrids.

KEYWORDS
balancing power, generation prediction, load prediction, microgrid

1 | INTRODUCTION

Distribution system operators face new challenges with the vast proliferation of distributed energy sources. The appearance of local generation leads to an active distribution grid, in which the number of possible system states is rising. Thus, the traditional centralized planning and operation methods are not adequate to provide electricity...
with proper power quality factors cost-effectively. However, the development of grid automation and innovative communication systems opens new opportunities to meet local electricity demand and supply in the context of the current state of the grid. The concept of microgrids unites these attributes and provides frequency regulation and energy management services for a local grid area. The possible benefits and value propositions of this concept were discussed by Reference 2.

Microgrids might need control reserve, on the one hand in order to keep their schedule running parallel to the main grid; and on the other hand, to sustain the frequency during island mode. The literature focuses on the latter case and does not deal with the reserve need of microgrids in grid-tied mode. Exceptionally, though, papers consider the imbalance of the microgrid, a settlement point between the microgrid and the main grid, and usually deploy an economic optimization of microgrid scheduling. Frequency control is the responsibility of the main grid operator while the microgrid is in grid connected mode. In contrast to this, the microgrid must control its frequency internally and thus keep the balance of generation and load in island mode. The primary (FCR—frequency containment reserve) and secondary (aFRR—automatic frequency restoration reserve) control levels known from the transmission system operator (TSO) frequency control are normally realized in the microgrid. However, the tertiary control level (mFRR—manual frequency restoration reserve and RR—replacement reserve) corresponds to the load distribution (scheduling). Consequently, the literature discusses primary and secondary control in microgrids if these two are differentiated at all. Secondary reserve is usually distinguished if the microgrid offers a reserve for the system operator. Primary frequency control can be realized by droop control as discussed in References 6, 7, and 9. Reference 10 proposes that these three hierarchical control layers are interdependent and have less sense in microgrids in the lack of control area partitions and thus different time scale controls. It concludes that primary, secondary, and tertiary microgrid control can be merged together based on continuous-time optimization approaches and implemented by the same averaging-based proportional integral (PI) controller.

The reserve need of microgrids is determined by the uncertainties of generation and consumption. Basically, three methods can be found in the literature for modeling renewable generation and residential load uncertainty: numerical methods (eg, Monte Carlo simulation that supports the determination of the probability distribution of the state variables in Reference 11); analytical methods that use convolution for the calculation of the random variables; and alternative methods (interval arithmetic, affine arithmetic, particle swarm optimization, or fuzzy). Some sources estimate the reserve need of the microgrid as 15% to 20% of the operating load. Others propose that all microgrid participants should provide their schedules and their maximum deviation from the schedule. The microgrid members pay for the control reserve (balancing energy) in proportion to their frequency control band that covers the microgrid system balancing energy and pay penalty upon more deviation than the contracted band. Under this market framework, the economic optimization of a given microgrid can be carried out.

In order to implement the microgrid concept in a local grid area, a wide range of studies proposed simulation frameworks and energy management system (EMS) concepts. In addition, a wide range of multiple energy sources (renewables, diesel generator, etc.), energy storage technologies (lead-acid, Lithium-ion battery, flywheel, etc.), and system configurations (DC, AC, hybrid microgrids) are discussed. Beyond the scientific importance of the results, the main disadvantage in most of the proposed microgrid frameworks is the lack of comparability. Moreover, the implementation of these programs is not designed in a concise way, despite the potential of modularity and scalability in such systems. Beyond the framework design, the EMS is responsible for the continuous, reliable, and optimal operation of the microgrid. Multiple aspects of existing EMS models are studied extensively in Reference 17, while 20 focuses on the proposed power balancing methods in microgrid control that highlight the importance of accurate power

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**Novelty statement**

In transition to a more flexible distribution grid operation, the importance of possible microgrid market value propositions is increasingly appreciated.

This paper introduces a unique simulation framework for testing and validating multiple operation issues of grid connected microgrids. The framework is widely adjustable and enables various control actions, for example, load shedding, demand response, power curtailment, and integration of battery energy storage systems (BESS).

Future research perspectives include physical demonstration and validation of possible ancillary service strategy planning for microgrids in a Hardware-in-the-loop environment.
demand, and supply forecasting as well as scheduling in the EMS decision making process.

Reference 22 estimates the temporal uncertainty level of load and renewable energy production in the microgrid. The proposed polytopic model helps to reduce reserve requirements and quantify the joint dynamics of forecast uncertainties. Formulate the problem as an economic optimization, considering the investment cost of a battery energy storage system (BESS) and the alternative cost of the required balancing energy. In addition to the optimization of microgrid reserve needs, a deeper integration and alternative value propositions of microgrid operation are assessed in several studies. Model predictive control (MPC) is widely used in the literature. In Reference 19, MPC and installed battery capacities enable the potential for the microgrid to provide ancillary services for the grid operator. The total earned revenue reached 12.03% of the operational cost, but the simulation was validated considering only the (USA) market conditions. Reference 24 focuses on possible BESS scheduling optimization techniques (without microgrid integration) to support utility grid operation and provide energy arbitrage, primary, and secondary control on the intraday time horizon. Despite the promising results, this method has the same minor deficiency as it cannot easily be adopted to the European context.

Despite the introduced methods, the authors realized that sometimes the dynamics of unbalance are modeled roughly. In several studies, a so-called uncertainty parameter describes the resulting unbalance of the system based on the historical dynamics of photovoltaic (PV) energy production, electric vehicle (EV) charging, residential load, etc. These articles conclude that (a) the individual and inter-temporal (e.g., joint distribution, convolution) correlations of these entities cannot be investigated; (b) this and may result over-conservative estimations. Moreover, in some papers uncertainty is modeled in a more robust way. In Reference 28, the renewable power output was implemented considering only clear-sky scenarios, while Reference 29 applies a constant value to describe the uncertainty of both PV systems and wind turbines.

The aim of this paper is twofold:

- A novel modular microgrid simulation framework concept is introduced that enables the replaceability of grid topology, connected entities, EMS, and even handles both software-driven and physical models;
- Secondary and tertiary reserve needs of the microgrid were also estimated based on confidence intervals that had not been found in the literature.

The scope of this paper is the investigation of microgrid internal reserve needs in grid connected mode in the presence of PV generation without battery energy storage. The implementation of various optimization algorithms and microgrid configurations is out of scope of the paper.

The remainder of the paper is structured as follows. Section 2 presents the simulation framework and the related modules. Section 3 shows the reserve need calculation of the modeled microgrid based on the prediction errors. Finally, the results are evaluated in section 4, complemented by further research plans.

## 2 | MODULAR MICROGRID SIMULATION FRAMEWORK CONCEPT

Complex microgrid modeling takes into consideration various aspects (technical, economic, communication, etc.) and requires the solution of optimization tasks. The aim of the present research is to demonstrate the operation of a framework for the implementation and testing of microgrid control algorithms, while using various predictors and providing control over generators and consumers of the microgrid.

A simulation framework was developed in order to maximize the benefits of individual platforms. Power system simulation was carried out in DigSILENT Power Factory 2020, which provides an overall functional integration of various modeling and simulation tools, making the framework easily adaptable for other research goals. Other algorithms were implemented in MATLAB 2019b (without an additional toolbox), benefiting from high computational performance and easy accessibility. The framework is designed to provide an interface and an opportunity for data exchange between the two environments. As both computer applications can be scripted using Python, five-module framework was created in this language (GenPred, LoadPred, LoadPred global, Loadflow, Opt), shown in Figure 1.

### 2.1 | Simulation framework

Three modules are implemented in MATLAB. A generation prediction (GenPred) module is used to forecast the PV electricity generation within the microgrid. The module receives initialization data (InitPar) and creates a predicted generation dataset (PredRes) with a preset temporal resolution. The GenPred module is detailed in section 2.1.3. The target function of microgrid control can be realized through the optimization module (Opt).
Another module (LoadPred_local) is responsible for estimating future consumption values of local consumers in the microgrid, using initialization data. The predictor algorithm uses a bottom-up approach and creates forecasts with preset temporal resolution. The module is discussed in detail in section 2.1.2.

The third MATLAB module (LoadPred_global) is used for the representation of the power system environment, in which the microgrid is located. The top-down short-term load forecasting algorithm is capable of using different architectures (temperature regression, temporal autoregression, and multilayer perceptron or radial base function). Its output is the time-series data of the total consumption of the main grid.

Within DIgSILENT PowerFactory, an iterative quasi-stationery simulation was used, based on load-flow (LoadFlow) functionalities. A representative network model has also been created (see section 2.1.1.) in this environment, which can be replaced by any other imported model later.

The initialization parameters of each module are discussed in the dedicated chapters of the modules. The data exchange and communication between the different platforms are provided by the MATLAB and DIgSILENT application programming interfaces (API). For this reason, the program execution is managed by the main program of the python framework.

The looped iterative structure used by the simulation is showcased in Figure 2. The simulation framework incorporates two different modeling environments connected via a python interface. The flowchart also indicates in which modeling environment each step takes place. After initialization, a looped iterative process begins for each timestep of the simulation timeframe. First, a preliminary load flow calculation is carried out to determine the initial state of the system. Based on its results and the generation and load predictions, an optimization module calculates the control commands that determine the active state of the system. After these control interventions, the load flow module is called again to reveal possible limitations of the control system and to store the final results.
results for later evaluation. The same goes on in each timestep until the end of the simulation.

2.1.1 | Network model

The aim of computer modeling was to create a sample network that gives a realistic representation of the Hungarian distribution network while allowing the study of future microgrids. For this reason, a computer model consisting of low and medium voltage distribution networks was created in the DIgSILENT PowerFactory environment.

The model is based on a real Hungarian distribution network. The topology of the network, including the length of the segments, the consumer’s connection points, the type (cable or overhead line), and cross section of the lines were used as the basis of the computer model.

However, some practical simplifications were also applied. Considering that the main aim at this early stage of the work was to carry out balanced, three-phase Load Flow calculations, only 3 phase line models were used in the low voltage distribution network, even if the real network counterpart was asymmetrical, for example, had single-phase line sections. Since only an insignificant fraction of the lines are built of such an asymmetrical type, this simplification is of little consequence. Nevertheless, the model is prepared to deal with unbalanced situations in subsequent scenarios, which only requires the changing of the parameters of the line segments in question.

Regarding the consumers, the data available varies in quantity and quality as well. The following facts are known: (a) the aggregated number of consumers connected to a node directly or indirectly (via an MV/LV transformer), (b) their annualized advance in each consumer category (pre-categorized united profile curves). Furthermore, the annual energy consumption of each individual consumer in each consumer category is available in the low voltage area. However, the location of their point of common coupling (PCC) along the feeder is unknown.

Some assumptions and simplifications were also made while creating the consumer models. For the sake of simplicity, the consumers connected to the same node and belonging to different consumer categories were aggregated and represented with a single load model. However, the residential loads were exempt from this simplification, as well as the switched loads. The individual modeling of these two categories allows us to study different demand side management solutions. According to this, the following consumer categories were distinguished and used in the final network model:

- R: residential;
- S: switched;
- C: commercial (including all the consumer profiles not belonging to the previous two categories).

The validation of the network model was carried out using static load flow simulations. Some details regarding these simulations are provided in the following sections.

For modeling purposes, a distribution network mainly consisting of overhead lines was selected. The substation supplying this distribution area was not modeled in detail. The total length of the low voltage feeder is 34.76 km as in Table 1. 33.8 km of this is overhead line, a mere 1 km is the total length of the cable sections. The number of the residential, switched, and commercial consumers connected to this feeder directly or indirectly is 2386, 1268, and 113, respectively. The annual active energy consumption of these consumers is 5158, 1370, and 1606 MWh, respectively.

The annual energy needs of the consumers connected to the network are given in Table 2, while the number of consumers belonging to each group is given in Table 3.

Beyond the showed grid parameters that are needed for a coherent network model, additional consumption and energy production values are necessary for a convergent loadflow simulation in the first phase of the framework execution (see Figure 2). Both time series are merged in one document and read by the program to meet initial conditions of execution.

| TABLE 1 | Main parameters of the LV network model discussed in detail |
|---------------------------------|-----------------|----------------|
| LV feeder 1 | LV feeder 2 | Total |
| Total length [m] | 2021 | 600 | 2621 |
| Cable [m] | 449 | 44 | 493 |
| Overhead line [m] | 1572 | 557 | 2129 |

| TABLE 2 | The annual consumption of the consumers connected to the LV network by consumption category |
|---------------------------------|-----------------|----------------|
| LV feeder 1 | LV feeder 2 | Total |
| Residential [MWh] | 230.14 | 107.72 | 337.86 |
| Switched [MWh] | 62.24 | 37.34 | 99.57 |
| Commercial [MWh] | 20.94 | 6.46 | 27.40 |
| Total [MWh] | 313.32 | 151.52 | 464.84 |
2.1.2 | Load predictor

Predicting local consumption is essential, as the network model mainly consists of residential consumers (profiled consumers without time-series metering). Moreover, the relatively small number of consumers makes the use of “average” load profiles unfeasible. The term local in our case means around 1 to 150 consumers; load flow calculations need household level consumption. Reference 30 studies a single household’s hourly consumption using a variety of methods (eg, neural network, k-nearest regression, random forest, statistic distributions, etc.). This study proves that even replaying the last day’s consumption is not necessarily worse than other methods. Consequently, the prediction error is at a different scale than in the case of transmission networks. Furthermore, a good average error does not necessarily mean a good representation of load dynamics. Numerous articles have been published in recent years (eg, References 31-35) for the prediction of single households’ hourly load, but there is no universal and best method.

Thus, a load predictor was developed for the framework dealing with this specific problem. Top down methods (eg, neural network, support vector machine, distributions, etc.) have been preferred, though these cannot properly capture the load dynamics and time dependency either—due to the small number of consumers. Bottom-up methods, which are based on equipment usage patterns in households, are not feasible, because these need very detailed social parameters that are not practical to collect. Replaying load behavior of previous days as a prediction is not feasible either, because—in general—distribution networks do not (yet) have the required monitoring infrastructure. Moreover, this method is not suitable for the planning of networks, as future states do not have measured values.

Therefore, real household measurement samples and some basic parameters from the model network (yearly consumption, geographic location) were used in this study.

The load predictor function uses a core database comprising hundreds of categorized load profiles. These profiles are individual quarter-hourly measurements of household consumption data for a full year. Thus, the load predictor takes into account seasonality, yearly consumption, and also geographical location (eg, suburbs, rural).

In order to make the method efficient, not only the algorithm itself, but also to the utilized set of load profiles are important. A representative dataset was acquired for the chosen location.

The geographical location is fixed in the current state of the study; that is, the feeders under examination are assigned to a geographical location; therefore, it does not change during the simulations. The following properties were the variables for the algorithm:

- Expected yearly consumption of the household (annualized advance);
- Type of day (ie, weekday, Saturday, Sunday / national holiday);
- Weekly, monthly, and yearly seasonality;
- Time.

The prediction is done on a household basis, so several sub-predictions are carried out for every simulation time step. One pass evaluates the step’s current parameters (see below) for every simulated household individually.

The implemented MATLAB algorithm is capable of predicting a single quarter-hourly power value (in W) for each residential consumer. Therefore, the input parameters for every time step and household are:

- Expected yearly consumption in kWh;
- Type of day—enumeration;
- Prediction day—sequence number in year (ie, 1—first January, 365—31st December);
- Prediction time—sequence number of quarter hour (ie, 1:00-0:15; 96-23:45-24:00).

The algorithm filters the profile database and gets samples from the appropriate candidates considering also the time of day. The summary of the required steps is as follows.

1. Is the household’s predicted consumption under the critical limit? (Yes—return 0 W prediction; No—continue.)
2. Is the household’s predicted consumption under the threshold? (Yes—triple the tolerance; No—continue.)
3. Select profiles where the expected yearly consumption differs no more than the tolerance percentage from the predicted yearly consumption.

### Table 3: The number of the consumers connected to the LV network by consumption category

|                | LV feeder 1 | LV feeder 2 | Total |
|----------------|-------------|-------------|-------|
| Residential    | 99          | 40          | 139   |
| Switched       | 34          | 23          | 57    |
| Commercial     | 1           | 1           | 2     |
| **Total**      | **134**     | **64**      | **198** |
4. Select the available days from the selected profiles. These are the days that have the same type as the predicted day's and are close to the predicted day's date. This latter condition means a date range that is defined by the tolerance for day parameter (December continues with January regarding the calculation of this range).

5. Randomly choose one quarter-hourly value from the selected profiles and days (the quarter-hour is the same as the predicted one).

6. Convert the consumption value to equivalent power value for that quarter hour.

All the above are done for every residential consumer in the model network.

The algorithm also needs some constants, which help to achieve better results. Exact values used for the present study are also given (in parentheses).

- Tolerance for expected yearly consumption: The allowed difference between the predicted household's and the base profile's expected yearly consumption (10%).
- Threshold for tolerance limit: A kWh value (typical annual electricity consumption) under which the percentage value for the above-mentioned tolerance is tripled in order to avoid over-fitting (800 kWh).
- Critical limit for expected consumption: A kWh value under which the predicted consumption is always 0 W. These consumption levels are very low, no representative profile can be used for this scenario (200 kWh).
- Tolerance for day: The allowed difference between the predicted day and the base profile's day. The type of day is nevertheless respected (7 days).

2.1.3 | Generation predictor

Solar power forecasting represents a crucial tool for uncertainty management to ensure system stability. For this reason, the literature discusses a wide range of powerful load prediction methods and performance comparisons. Spatial and temporal resolution aspects give a good insight into how to classify and set the limitations of these algorithms. The day-ahead time horizon and the high spatial resolution clearly set out neural networks as proposed methods.

In the case of an intermittent energy producer, there is a crucial point to consider the environmental parameters during the power prediction process. For this reason, the implemented PV load predictor consists of a clear sky irradiance estimator (incl. a physical model) and a pretrained neural network that uses the proposed logical structure of Reference 38. The estimator is implemented by a physical model, which predicts AC output power using PV panel solar irradiance (see Figure 3).

The inputs of the neural network are the output of the physical model and the environmental parameters (e.g., cloudiness) for the final PV plant power output estimation. During the training process, the neural network learns a nonlinear mapping using physical model (clear sky) results in cloudless scenarios and a complex weighted result of the inputs in all other cases.

The input data for the model validation were provided by the Hungarian Meteorological Service. The Weather Research and Forecasting (WRF) based prediction has a day-ahead time horizon and a 15 minutes resolution. For the verification of the prediction accuracy, a historical dataset was collected from a PV plant near Mórahalom, Hungary with 69 kWp nominal power.
The aim of the physical model is to give a prediction, which uses the ecliptic and the periodical change of solar irradiance.

For this reason, the model manages the following aspects:

- The temporal change of solar irradiance at a certain geographical point;
- Electrical parameters of a PV power plant (e.g., losses, panel features);
- Shading effect of panel rows;
- Solar irradiance changes due to the eccentricity of earth path around the sun.

The MATLAB implementation was divided into certain functions for the manageable coding, and it consists of the following logical parts:

- Clear Sky model;
- Shading effects;
- Ecliptic features;
- PV plant technical parameters;
- Aggregated clear sky PV power output.

The neural network part of the load predictor uses a simple feedforward model with one hidden layer, sigmoid activation functions, and backpropagation. The layer node numbers are 5, 3, and 1, respectively.

The training loop ends when the network can predict the AC power output with the best accuracy. Then the predictor function generates power output values using test set parameters and the weights of the trained neural network.

The given results are stored in a variable, including the real measured output value for the comparison. The use of learning algorithms sometimes might lead to unexpected results, for example, positive predicted power during night hours. Such possibilities have been logically avoided; thus, the error of the predictors is zero in these periods.

The validation interval lasts from 1st July 2017 to 10th September 2018. The neural network was trained with the following input parameters:

- Thickness of snow (cm);
- Windspeed (m/s);
- Cloudiness of the sky (%);
- Temperature (°C);
- Physical model AC power prediction (kW).

With the aim of a computationally efficient framework concept, the neural network is trained before the execution of the simulation. Therefore, the solar energy production forecast process (see Figure 2) utilizes only the weights of the pre-trained neural network. The pre-train and the forecast time series are separated in time.

2.2 Calculation of balancing needs

As pointed out in the introduction beforehand, the authors did not find any reference calculation of the required primary reserve capacity in the literature specifically for microgrids. Therefore, the methodology used by ENTSO-E has been applied that considers the allowed maximal dynamic and quasi-stationary frequency deviation for primary control reserve procurement. In the case of the modeled microgrid, the maximum load deviation resulting in ±800 mHz dynamic or ±200 mHz quasi-stationary frequency deviation could be determined by simulation or by testing in the case of a real microgrid. As a reference, the maximum load deviation in the ENTSO-E region is 3000 MW, which is approximately 0.5% of maximum load in the synchronous area (the highest and lowest load values have been 264.157 and 589.716 GW, respectively, in 2018 according to Reference 39).

As for the secondary reserve provision, two ENTSO-E recommendations can support the microgrid secondary level reserve planning. These are the probabilistic risk management sizing approach, and the largest possible outage (generation unit or power infed, “control largest incident") as the minimum need, because the constants of the empiric noise management sizing approach valid for ENTSO-E are probably not adequate for microgrids and would be difficult to determine. Certainly, the probabilistic methods provide the best approximation. However, they require historic data of control reserve need in each time unit. That is why the microgrid simulation was necessary, generating this data time series. The difference of the microgrid generation and consumption corresponds to the balancing energy need. Therefore, the reserve estimation error is based on the forecast errors of the generation predictor and the load predictor modules. In the case of the modeled microgrid, this means PV generation forecast and the forecasted consumption of the consumers. However, there are other methods, which focus on the most economical/profitable operation of a microgrid, also considering reserve provision to the TSO. However, such examinations are to be carried out in a later phase of the research.

A previous test of the forecast modules was available in 15 minutes resolution in the case of PV generation and in hourly resolution for load prediction, which is not enough for the reserve error estimation, as consumption and generation must be balanced in each moment. The most significant PV generation estimation error is caused by the
estimation of irradiation. The authors in Reference 41 proposed to estimate PV generation by fitting a probability distribution function to the irradiation time series that gives the probability of each irradiation value. Finally, this result was converted to a PV power output value. Multiplying the irradiation, its corresponding probability and the irradiation characteristics define the distribution of PV generation. Reference 11 described another solution for the estimation of PV generation, determining the consumption and the resulting balancing need by dividing the probability distribution function into intervals and applying the roulette-wheel method.

Here, a third solution was applied that is based on the net energy need and the errors of the PV generation forecast and the load estimation similar to Reference 12, because this applies less approximation compared to other methods. Furthermore, the input data can be easily produced by the modules planned for the microgrid operation. According to the stochastic approach of the novel System Operation Guideline, the 99% confidence interval determines the minimum amount of the FRR + RR procurement. While 95% probability must correspond to the sum of the aFRR and mFRR, out of which the aFRR amount can be determined by the reserve need at the 70% confidence level.

3 | THE ESTIMATION OF THE BALANCING POWER NEEDS

To analyze the operational characteristics of the framework and introduce the balancing energy calculation model, the authors have examined an approximately one-year simulation from 1st July 2017 to 10th September 2018.

In the following, detailed results are presented, emphasizing the magnitude and temporality of prediction errors, and the thus arising balancing energy needs. All results are given per units (p.u.), the base unit for power was the average power consumption of the modeled microgrid. The errors are referred to the measured value that was used for the simulation. The predictors received the previous measurements, and the prediction is compared to the actual measurement. The algorithms are used to predict the next day with a quarter-hour resolution.

3.1 | Qualitative analysis of prediction errors

3.1.1 | Load predictor performance evaluation

The histogram of the prediction errors is shown in Figure 4. Errors with the highest probability are slightly positive (the median of errors is 0.0046 p.u.), meaning that the algorithm tends to slightly overestimate the consumption (mean is −0.0051 p.u.), for the studied period. This extent is acceptable, especially compared to the deviation of the distribution.

Figure 5 shows the temporality of the distribution utilizing Matlab’s BoxPlot feature. The slight overestimation mentioned above comes from the outliers. Temporal distribution indicates that errors are spread on a wider range in hours with larger consumption. The RMS error of the predictor is 0.1031. Thus, the error is independent of the actual consumption, except for the late night—early morning period when it is smaller. The fewer the households and the larger the expected yearly loads are, the larger the chance of outliers is. Since this microgrid is not that large—from a power system perspective—we can observe these outliers.
3.1.2 | Generation predictor performance evaluation

The probability density and temporality of the PV generation prediction errors are different, compared to those of the load predictor. It can be seen in Figure 6 that the histogram resembles a Bell curve, although it is not perfectly matching. Local weather heavily impacts generation, which in turn distorts the distribution. The deviation from a Gaussian distribution also implies that the prediction could be enhanced with a better weather forecast. Note that only data of daytime were considered here for the histogram, because there is no generation during these times for which the prediction is accurately zero. Considering the full year, median and mean of the error distribution are 0 and \(-0.0226\), respectively. Solar generation is, therefore, also overestimated, and the deviation of the distribution is larger than that is for the load prediction. This is also acceptable compared to the deviation of the distribution. The root mean square (RMS) error of the predictor is 0.1446. As shown in Figure 7, the temporality of the predictor tends to overestimate PV generation during sunrise and sunset hours, and a more symmetrical error is seen during the day. The errors spread out on a wide range: the results reflect that weather is hard to predict for a small geographic area.

3.2 | Balancing power needs

Balancing power needs is basically the deviation from schedule, and since schedule is dependent on forecast (prediction) of the microgrid, improper prediction of load and PV generation causes balancing need in a microgrid most of the time. The amount of necessary balancing energy was calculated as the signed sum of load prediction error and generation prediction error of every moment. If any of those showed tendentious errors (skewed distribution), or if the magnitude of one type of error significantly exceeded that of the other, it would lead to very unbalanced power needs. In the examined case, no such issues are seen; balancing...
power needs arise in both upwards and downwards directions, and the occurrence of those is similar. Figure 8 shows the distribution of the balancing need, which resembles a Gaussian distribution, but is much narrower. The mean balancing power need is almost symmetrical: 0.0175 p.u. for every quarter-hour arises, which can be converted to 0.182 kWh balancing energy. The RMS error is 0.2145 p.u.

Temporality of the error reflects the different nature of the predictors (Figure 9). The higher error and thus the growing balancing need of daytime hours is the result of PV generation. At noon, balancing need almost has the same magnitude as the generation prediction error value. The balancing need is increased when PV generation is present, compared to load prediction error alone.

### 4 | DISCUSSION

Balancing power and reserve needs calculated according to EU’s System Operation Guideline are shown in Table 4. For a 99% confidentiality level, 1.32 p.u. downwards reserve and 1.21 p.u. upwards reserve is necessary. These can be divided into 0.22 p.u. aFRR, 0.59 p.u. mFRR, and 0.51 p.u. downwards RR reserve as well as 0.22 p.u. aFRR, 0.55 p.u. mFRR, and 0.44 p.u. RR upwards reserve.

|                | aFRR  | aFRR+mFRR | aFRR+mFRR+RR |
|----------------|-------|-----------|--------------|
| Downwards [p.u.] | 0.22  | 0.81      | 1.32         |
| Upwards [p.u.]   | 0.22  | 0.77      | 1.21         |

TABLE 4 Reserve power requirements of the microgrid, based on balancing power needs

Daily and seasonal temporality of predictor errors (and thus balancing power needs) are worth considering in microgrid planning. The load predictor has shown rather uniform behavior during the examined one-year period. The only notable deviation was seen during winter months, where overestimation of consumption was more significant than in other periods of the year. In contrast, the PV generation predictor is prone to show seasonality, which is reflected in the underestimation of power during winter months and the overestimation during summer months. A combined result of these effects is shown in Figure 10.

Most of the examined period can be characterized by small balancing power needs. Therefore, more balancing reserve is kept than actually needed. However, this could also lead to the more frequent and pronounced activation of mFRR and RR during daytime than without PV generation. PV generation does change the picture, but it does it in a relatively predictable way. Thus, the authors suggest that extension and development of the balancing power calculation should consider temporality as well, for more effective provisioning of balancing reserves.

### 5 | CONCLUSIONS

In this article, a simulation framework is presented, which is designed to provide an interface between DIgSILENT PowerFactory and MATLAB, in order to assist the complex modeling of a microgrid. It is capable of predicting different consumption and generation scenarios and calculating network flows and voltages accordingly. The framework is also equipped with means to implement any further algorithms, which could interact with the load and generation taking into consideration different states of the network (eg, network constraint mitigation, loss optimization).

Here, the usage of the framework has been described, for the calculation of balancing power needs of a microgrid arising from the inherent error of load and generation prediction. It has been shown that despite the different characteristics of the predictor algorithms, cumulative errors tend to be balanced, which allows the use of the stochastic approach of the EU System Operation Guideline to determine balancing power needs. The calculations have proved that to cover aFRR and mFRR needs, approximately 0.8 p.u. has to be kept as a reserve. The efficiency of the presented approach can be further improved by taking into consideration both daily and
seasonal temporalities of the data. Moreover, the simulation framework was developed with the aim of physical implementation.

In the future, the local grid model will be implemented in a Hardware-in-the-loop (HIL) system keeping the interface for the different modules (load and generation prediction, optimization algorithm). Based on the presented results, the quasi-real simulations already open the opportunity to demonstrate a realistic microgrid operation. A further research goal is to develop and validate control strategies to reveal the market potential of microgrids on the market of ancillary services.

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