Effect of Short-term and High-resolution Load Forecasting Errors on Microgrid Operation Costs

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***Abstract*—The aim of this paper is to evaluate the effect of the load forecasting errors to the operation costs of a grid-connected microgrid. To this end, a microgrid energy scheduling optimization model was tested with deterministic and stochastic formulations under two solution approaches i.e., day-ahead and rolling horizon optimization. In total, twelve simulation test cases were designed receiving as input the forecasts provided by one of the three implemented machine learning models: linear regression, artificial neural network with backpropagation, and long short-term memory. Simulation results of the weekly operation of a real residential building (HSB Living Lab) showed no significant differences among the costs of the test cases for a daily mean absolute percentage forecast error of about 12%. These results suggest that operators of similar microgrid systems could use simplifying approaches, such as day-ahead deterministic optimization, and forecasts of similar, non-negligible accuracy without substantially affecting the microgrid's total cost as compared to the ideal case of perfect forecast. Improving the accuracy would mainly reduce the microgrid's peak power cost as shown by its 20.2% increase in comparison to the ideal case.**

***Index Terms*—Battery, energy management, load forecasting, machine learning, microgrid, stochastic optimization.**

I. INTRODUCTION

The combined integration of renewable energy sources (RESs) and battery energy storages (BESs) in residential buildings creates controllable clusters of resources and electricity customers, which have been defined as grid-connected building microgrids (MGs) [1], [2]. The MG operator utilizes the controllable resources to achieve an MG energy scheduling i.e., an amount of energy exchange with the upstream connected grid at each time step, that will satisfy its operational targets.

The MG energy scheduling (also known as management or dispatch) has extensively been studied as an optimization problem in recent research [3]–[5]. As the literature review in [5] shows, it has often been formulated either as deterministic optimization (DO) or stochastic optimization (SO) problem; the latter in order to address uncertainties without enforcing conservative costly solutions, as is the case with robust optimization. Typically, MG resources are dispatched hourly within a look-ahead time horizon of 24 hours. However, the need to mitigate the effects of intermittent RES generation has motivated researchers to study intra-hour dispatch schemes. Since the problem uses a look-ahead horizon and requires forecasts of the uncertain input values (e.g., load demand) at each dispatch time step, it is obvious that there is a need for both *short-term* and *high-resolution* forecasts.

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Machine learning (ML) models such as neural networks (NNs) have successfully been employed to provide electric load forecasts in the last 30 years [6]. However, there has been a lack of studies that seek to satisfy the two-fold requirement, as only a few publications (e.g., [7]–[10]) have developed forecast models with a resolution of a few minutes.

The main contributions of this paper are:

- A scenario-based SO model for market-based energy dispatch of a grid-connected MG. The model combines look-ahead uncertainty with deterministic control to improve scalability and computational efficiency and is used to perform optimal dispatch under two solution approaches i.e., day-ahead (DA) and rolling horizon (RH), in which it is compared with its deterministic counterpart.
- The implementation of three load forecasting ML models, which gave input to both the DO and the SO models, based on real-world building demand data. Contrary to most studies, the load forecasting is both *short-term* and *high-resolution*. The forecast accuracies of the ML models were compared and the effect of their error was evaluated with standard stochastic assessment metrics.
- A detailed representation of the load uncertainty used in the SO problem including dependencies of the forecast error on time of prediction, time of occurrence of predicted value, and predicted time ahead.

II. MG ENERGY DISPATCH PROBLEM FORMULATION

This section presents the formulation of the SO model that is used to solve the energy dispatch problem of an MG with photovoltaics (PVs) and a BES. The outcome of the solution is a set of BES power set-points such that the MG customers maximize their economic benefits, while their power demand is supplied by the MG resources and/or the external grid.

A. Scenario-based SO Model

The objective of this model is to minimize the expected MG cost f^{SO} of the scheduling period over a number of scenarios with different load demand profiles. These scenarios represent the uncertainty due to the load forecasting errors. The MG cost consists of the expected cost of energy import c^{im}, the expected revenue of energy export r^{ex}, which is subtracted, the expected peak power cost r^{p} due to the charge of peak imported power from the main grid, and the BES degradation cost. In order to reduce the size of the SO problem and avoid scalability or solution tractability issues, which are common in SO, the BES control decisions are deterministic i.e., independent of the scenario. The MG import/export power

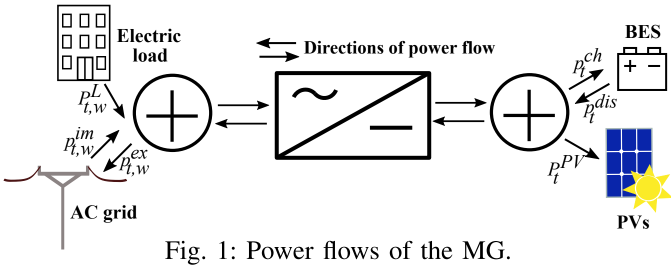

Fig. 1: Power flows of the MG.

from/to the grid at time step t and scenario w, which are denoted by the positive variables $p_{t,w}^{im}/p_{t,w}^{ex}$, are the stochastic decision variables of the optimization problem. Their values depend on the values of BES charging/discharing power rates p_t^{ch}/p_t^{dis} (deterministic, positive variables), PV power output P_t^{PV} (deterministic input parameter) and electric load $P_{t,w}^{L}$ (stochastic input parameter). The PV power output is deterministic i.e., a perfect PV generation forecast is assumed, to focus on evaluating the effect of the load forecasting errors on the MG costs.

1) Objective Function: The objective function is given by:

$$\min f^{SO} = c^{im} - r^{ex} + c^{p} + c^{B}, \tag{1}$$

where

$$c^{im} = \sum_{t \in \mathcal{H}} \sum_{w \in \mathcal{W}} \Pi_w (\Lambda_t + C_i) p_{t,w}^{im} \Delta t, \tag{2}$$

$$r^{ex} = \sum_{t \in \mathcal{H}} \sum_{w \in \mathcal{W}} \Pi_w (\Lambda_t + C_e) p_{t,w}^{ex} \Delta t. \tag{3}$$

The set of time disretization steps i.e., the scheduling horizon, and their duration are respectively shown by $\mathcal{H}$ and Δt in (2)–(3), while Π_w is the probability of occurrence of scenario $w \in \mathcal{W}$. Eq. (2)–(3) analytically present the values of c^{im} and r^{ex}, where Λ_t is the electricity wholesale market price, C_i is the grid charge for energy transmission, and C_e is the reimbursement fee paid by the grid operator as an incentive to reduce network losses. The cost r^p must satisfy

$$r^p \geq C_{pp} \sum_{w \in \mathcal{W}} \Pi_w p_{t,w}^{im}, \ \forall t \in \mathcal{H}, \tag{4}$$

so that it is linked to the expected maximum average (over Δt) $p_{t,w}^{im}$ of the dispatch horizon. The power-based grid tariff (scaled according to the chosen horizon) is denoted by C_{pp}.

2) Power Balance: As can be seen in Fig. 1, the PV and BES systems are connected to the upstream AC grid via a converter (here assumed to be lossless) with bi-directional operation. Thus, both the PV and the BES power output can be exported to the AC grid, whereas the BES can be charged through both the AC grid and the PV system as expressed in:

$$P_t^{PV} + p_t^{dis} - p_t^{ch} = p_{t,w}^{ex} - p_{t,w}^{im} + P_{t,w}^{L}, \forall t \in \mathcal{H}, \forall w \in \mathcal{W}. \tag{5}$$

3) BES Model: The model also incorporates the constraints related to the BES operation, which linearly link the BES's state-of-energy (SoE), denoted by the variable soe_t, and the cycle-based BES degradation (capacity loss) to the BES throughput. The model was presented in detail in [11].

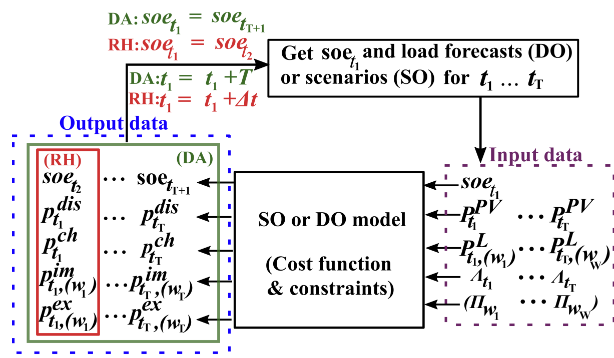

Fig. 2: Illustrative diagram of the MG energy scheduling solved in the DA and RH approaches.

4) Solution Approaches: The SO model and its deterministic counterpart can be solved either DA or using the RH approach, as can be seen in Fig. 2. The load forecast profiles and the distributions of forecast errors are updated after the time horizon is shifted either by a scheduling period in DA optimization or by Δt in RH optimization and are used as input to the optimization model. In DA optimization, the control decisions for the whole scheduling horizon are applied, whereas in RH optimization, it is only the next step control decisions that are implemented after each simulation; the rest of the BES operation set-points are discarded or they can be used in case of unexpected failures to update them.

B. Uncertainty Representation & Modeling of Forecast Errors

To represent the uncertainty associated with load demand in the SO problem, the forecast errors were assumed to follow Gaussian distributions. This is a common practice employed by many studies e.g., [3], [12]. For a more detailed characterization of the uncertainty in this paper, different probability distributions were used for each time step of the dispatch period. The parameters of the Gaussian distributions depended on the time when forecast results were acquired, the time when the predicted load values occur, and the predicted time step ahead, while they were obtained from testing the forecasting models with historical data and implementing curve fittings.

These distributions were used to generate scenarios with the Monte Carlo (MC) method i.e., random sampling of the input data, which were the load forecast values with the added noise to represent forecast error. The available forecast profile was treated as the base scenario and an error was generated by a Gaussian random number generator for each time step. The values of the base scenario were then adjusted according to these errors creating one future scenario of electricity load. This process was repeated to obtain multiple scenarios (see Fig. 3) and after applying a scenario reduction technique, a reduced set of scenarios was created with a different probability of occurrence assigned at each scenario. Scenario reduction contributes to reducing the size of the SO problem without substantially compromising the accuracy of the results.

III. Load Forecasting Using ML Models

The ML models used and tested for the load forecasting were: 1) a linear regression (LR) [6], [13]–[15] model, 2) an artificial NN (ANN) [16] with backpropagation, and a long

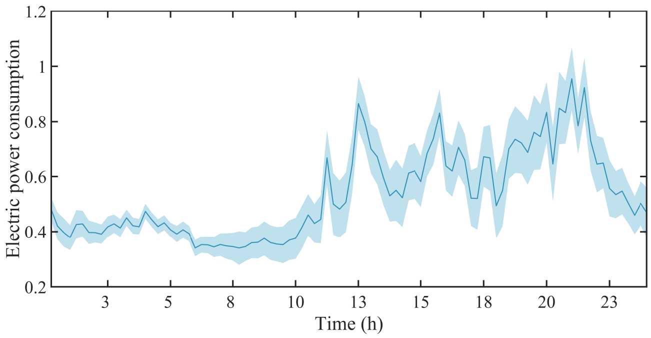

Fig. 3: Scenarios of electric load (given as ratio of the peak load). The base forecast is shown by the dark color line and one standard deviation is shown by the light-shaded areas.

short-term memory (LSTM) model [8], [9], [17], which is a type of artificial recurrent NN. For the development of these models only time-series historical data of electric load were used. This was decided after performing correlation analyses with weather data. The autocorrelation analysis of the load time-series was carried out to decide the input to the models, which was chosen to be the past 24 h load data so that there is a good compromise between quality and computation time.

The historical electric load data with a 15-minute time resolution were taken from the residential HSB Living Lab (HSB LL) building, which contains 29 apartments housing 40 residents and is located in Gothenburg, Sweden [18]. To optimize the performance of the ML models a training set of qualitative sequential data was created by pre-processing the load data to deal with issues such as missing measurements, measurement errors, and daylight saving time adjustments.

IV. Simulation Results and Discussions

The performance of the energy scheduling model was validated using the HSB LL building MG as the test system in the following simulation test cases:

1) Stochastic optimization solved day-ahead (SO-DA)
2) Stochastic optimization solved in RH (SO-RH)
3) Deterministic optimization solved day-ahead (DO-DA)
4) Deterministic optimization solved in RH (DO-RH)

In DA energy dispatch, an additional constraint is added to avoid having an empty BES at the end of the scheduling period. Typically, the SoE at the end is set to be equal [19] or very close [20] to the initial SoE. In this paper, the SoE at the beginning and end of the scheduling period was set to be 0.5 i.e., 50%. In DO, the index w is removed from the variables and parameters of the problem formulation and all expected values are replaced by their deterministic counterparts.

The MG consists of PV systems with a 13 kWp total capacity, a 7.2 kWh BES with 1.2 energy to power ratio, and a building with 32 kW peak load. For detailed information on the BES's parameters and the simulations' input data see [11]. The energy dispatch and the forecasts had the same time horizon of 24 h and the same resolution i.e., $\Delta t = 15$ minutes. The simulations were performed for a week in December, 2018 using the historical load profile as the base scenario for SO and as the realized scenario for DO. In the studied week, there was minimal PV production to effectively eliminate the impact of the approximation due to the perfect PV forecast assumption and enhance the accuracy of the results. Future studies can consider using ML models for short-term and high-resolution PV forecasting; note, however, that the ML techniques and the training data would be quite different compared to load forecasting, as short-term PV forecast is all the more based on sky imagery mechanisms [21].

TABLE I: MAPEs for the ML Models and the Base Line Model over the First Four Quarters and on All Prediction Tests.

Model	15 min	30 min	45 min	60 min
Linear Regression	7.79%	9.63%	10.25%	10.60%
Artificial Neural Network	8.10%	9.77%	10.25%	10.06%
Long Short-term memory	8.93%	9.98%	10.45%	10.73%
Base Line	8.28%	11.14%	12.43%	12.26%

A. Performance of ML Models

The performance of the ML models was evaluated using the mean absolute percentage error (MAPE), which is shown in Table I for the first four quarters. These MAPEs were derived by computing the MAPE over all of prediction tests (a prediction test was run for each time step amounting to a total of 365x96 tests for each ML model). The models were also compared with a base line model, i.e., a naive and empirical approach which assumes that the coming four quarters maintain the load value of the current quarter.

As shown in Table I, the base line model performed equally well, or even better, than the ML models in the 1st quarter. However, it rapidly lost precision as expected, and already performed worse than the ML models in the 2nd quarter. The LR model, which had the lowest MAPE in the first two quarters, was outperformed by the ANN in the 4th quarter.

The LR model also had slightly worse performance than the other two ML models considering their average MAPE for the 24 h time horizon of the forecast calculated over all prediction tests, as can be seen in Table II. The average MAPE of this study was compared with the MAPE of other studies with similar applications of these ML models at the highest resolution that was found in literature. The comparison showed that the MAPE of the ANN model could be lower than some of the other studies that implemented an ANN. Works that applied LSTM for high-resolution forecasting were found to have lower average MAPE than this paper, which could probably be attributed to the different use of the buildings.

To corroborate the common assumption that the probability distribution of the load forecast error takes a Gaussian form the errors for each prediction test of the ML models were recorded and presented as a histogram in Fig. 4. As can be seen, the results verified that the probability distribution of the error can be well approximated by a Gaussian distribution. As for the dependencies of these errors on the factors described in Section II-B, these can be visualized in Fig. 5. The big deviation of MAPE recorded for the first 1,5 hour and for the hours between 00:00 and 06:00 demonstrates the need to have different probability distribution at each time step.

TABLE II: Mean MAPE over 24 h Time Horizon.

Model	MAPE	Resolution	Application	Reference
LR	12.05%	15 min	HSB LL	This paper
LR	3.52-4.34%	1 h	Indonesian Province	[13]
LR	1.00-2.63%	1 h	Poland's electric power system	[14]
LR	5.20-6.10%	1 h	782 households	[15]
ANN	11.91%	15 min	HSB LL	This paper
ANN	15.32%	1 h	Building complex	[22]
ANN	7.19%	1 h	Campus building	[16]
ANN	14.50%	1 h	69 households	[17]
LSTM	8.58%	1 h	69 households	[17]
LSTM	5.35%	15 min	School building	[8]
LSTM	6.45-14.01%	10 min	Building	[9]
LSTM	11.97%	15 min	HSB LL	This paper

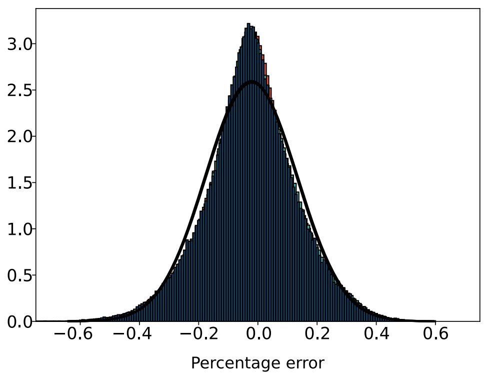

Fig. 4: Histogram of percentage error for all prediction tests. The solid line is a Gaussian distribution fitted to the data.

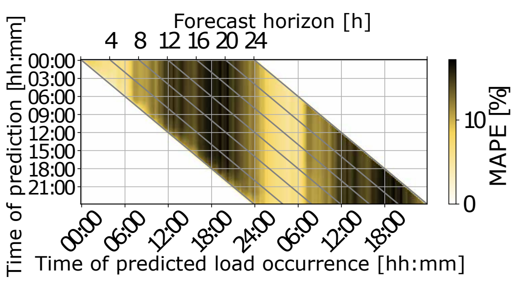

Fig. 5: Color chart of MAPE in relationship with time of prediction (y-axis) and time of the load value occurrence (x-axis). The slanted lines through the chart show the time ahead.

B. Effect of Forecast Errors

The costs related to MG energy dispatch can be seen in Table III, where all three ML models were used to give input to each test case. As can be seen from the total cost f, similar results were achieved with DO and SO and the same was observed comparing DA and RH solution approaches. These were perhaps counter-intuitive outcomes, as judging from the non-negligible forecast errors (see Fig. 6), one would expect worse performance from DO and DA schemes. Still, all the solutions based on forecasts did not deviate more than 1% from the solution in the ideal case of DO assuming perfect forecast. Based on this, it can be concluded that the generated forecasts for that week were sufficiently good to be used in DO. Note that the DO might not perform as well as SO, however, if different realized scenarios are considered.

TABLE III: Cost [$] of MG Energy Dispatch for a Week.

	f	$c^{im} - r^{ex}$	c^{p}	c^{B}
SO-DA (LR)	145.58	134.17	11.24	0.17
SO-DA (ANN)	145.51	134.17	11.24	0.10
SO-DA (LSTM)	145.50	134.18	11.23	0.09
SO-RH (LR)	145.39	133.95	11.24	0.20
SO-RH (ANN)	145.41	133.90	11.24	0.27
SO-RH (LSTM)	145.30	133.88	11.24	0.18
DO-DA (LR)	145.47	134.18	11.24	0.05
DO-DA (ANN)	145.51	134.18	11.24	0.09
DO-DA (LSTM)	145.44	134.18	11.23	0.03
DO-RH (LR)	145.40	133.96	11.24	0.20
DO-RH (ANN)	145.47	133.96	11.24	0.27
DO-RH (LSTM)	145.35	133.96	11.24	0.15
DO-DA (perfect forecast)	144.62	134.13	9.78	0.71
DO-RH (perfect forecast)	143.84	133.52	9.86	0.46

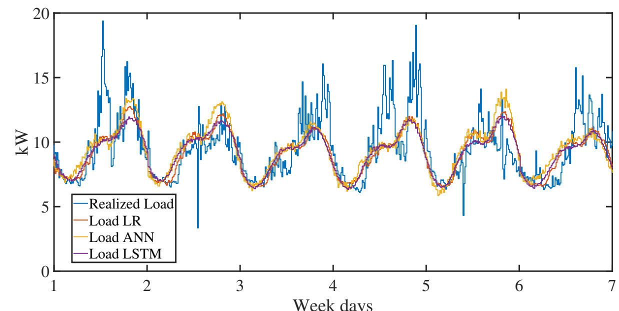

Fig. 6: The load forecasts obtained by the ML models.

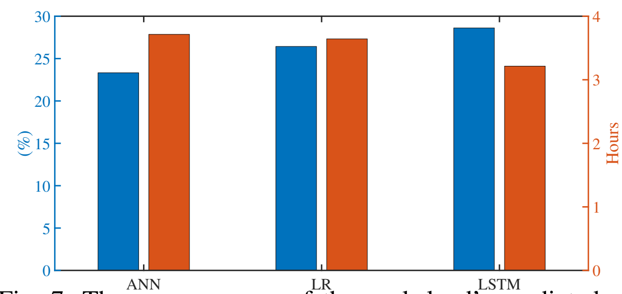

Fig. 7: The average error of the peak load's predicted value (left y-axis) and time of occurrence (right y-axis) over the simulated week for each ML model.

The higher cost of the test cases that used forecasts in comparison to the ideal case was mainly due to c^p, which accounted for about 8% of the total cost f and was increased up to 20.2%. This can be explained by the difficulty of the ML models to accurately predict the value or the time of occurrence of the daily peak load (see Fig. 7) and by the low potential for energy arbitrage, which, combined with the low PV output, led to minimal variations in the energy costs.

The value of SO and the effect of the forecast error can also be assessed by two stochastic metrics which use DO as a comparison benchmark [23]: the expected value of perfect information (EVPI) and the expected cost of ignoring uncertainty (ECIU). Defining $f_w^{DO,PI}$ as the cost obtained by DO assuming perfect forecast i.e., perfect knowledge of the load profile of scenario w, the value of the EVPI is obtained by subtracting by f^{SO} the expected cost computed as the weighted sum of the costs $f_w^{DO,PI}$ over all scenarios:

$$EVPI = f^{SO} - \Pi_\omega \sum_{w \in \mathcal{W}} f_w^{DO,PI}. \tag{6}$$

TABLE IV: SO Metrics

ML model	EVPI	ECIU
LR	3.13%	0.29%
ANN	3.19%	0.32%
LSTM	5.69%	0.30%

The ECIU value is obtained by the weighted sum of the difference between the cost of the SO solution and the cost of the DO solution for each scenario f_w^{DO}, where the forecast is naively treated as perfect information ignoring uncertainties:

$$ECIU = \Pi_\omega \sum_{w \in \mathcal{W}} (f_w^{DO} - f^{SO}), \tag{7}$$

Assuming that only one of these scenarios is realized, the deterministic cost will be higher than the expected cost over some of the scenarios. An example of these metrics for the DA energy scheduling is given in Table IV.

The EVPI and ECIU are given in % of the total cost of DO-DA with perfect forecast and have been calculated for all ML models assuming that the base scenario was realized for the calculation of ECIU. The almost similar costs of SO and DO in DA or RH solution approaches (see Table III) indicated that there was very little cost of ignoring uncertainty i.e., the value of SO was trivial. This was validated, as ECIU in Table IV was less than 1%. Although all ML models had a similar ECIU, LSTM had a higher EVPI, which implies that it could not handle uncertainties as well as the LR and the ANN models.

Regardless of the low ECIU, SO was favored for the 15-minute energy dispatch of this study thanks to the fast execution time of the scenario generation and solution of the SO problem. This time was approximately 15 sec in total for simulations performed on a PC with 4.2 GHz Intel(R) Core(TM) i7-7700K CPU and 64 GB of RAM. However, it should be noted that the SO problem could become computationally heavy if a higher number of scenarios, a higher resolution, or a more complex optimization model (e.g., due to more MG resources) are considered.

V. Conclusions

This paper presents an optimization model to solve the energy dispatch problem of a building MG using short-term and high-resolution load forecast based on three ML models: LR, ANN, and LSTM. The main conclusion that can be drawn from the simulation studies, which compared DO and scenario-based SO problem formulations solved in RH or DA, is that, even without high computational requirements or extreme forecasting precision, a near-optimal dispatch can be achieved with an MG total cost no higher than 1% of the optimal cost i.e., if the up to 12% daily MAPE of the forecasts could be eliminated. It was also shown that more accurate forecasts could mostly contribute to reducing the peak power cost, which was 20.2% higher than the optimal. All ML models resulted in almost equal MG operation costs, however, a higher EVPI was calculated for LSTM showing that this model was less effective in handling uncertainties. Using simpler forecast models such as LR and simplifying approaches such as DO or DA dispatch did not increase the associated costs, which was a promising result, as these simplifications could be used in joint operation and planning studies to simultaneously enable faster and sufficiently accurate solutions.

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