Received 5 May 2018; revised 7 September 2018; accepted 7 October 2018. Date of publication 1 November 2018; date of current version 11 December 2018.

Digital Object Identifier 10.1109/JPETS.2018.2878329

Reduction of Forced Outages in Islanded Microgrids by Compensating Model Uncertainties in PV Rating and Battery Capacity

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ABSTRACT Energy management systems for islanded microgrids often rely on predictions of energy availability and usage. Such predictions can be used to plan actions, such as shedding non-essential loads, so that critical loads continue to be served. However, uncertainties in the prediction models may lead to incorrect decisions, and subsequently jeopardize reliable operation of the microgrid. For a photovoltaic (PV) and battery based microgrid, uncertainties in the PV rating and the battery capacity model parameters can lead to otherwise avoidable outages. In this paper, techniques have been developed to identify and compensate for such model uncertainties. The approach uses differences between the actual and predicted data sequences to determine compensation factors to improve prediction accuracy. The developed techniques account for operating condition changes automatically, and no additional sensors are needed for their implementation. The method has been evaluated using data from rooftop irradiance and temperature sensors and the corresponding forecasts. It has been shown that the proposed techniques can improve the accuracy of the predictions and hence lead to more effective energy management decisions. Together with a pre-emptive load shedding strategy, the total outage time of the microgrid can be shortened by as much as 11% for the chosen scenario.

INDEX TERMS Energy management, photovoltaic systems, microgrids, prediction model uncertainties.

NOMENCLATURE

$\mathcal{B}$	Battery unit dataset
$E_{\text{batt}}^{\max}$	Battery capacity (Wh)
$E_{\text{batt-0}}^{\max}$	Uncompensated battery capacity (Wh)
$\mathcal{F}$	Interpolated forecast dataset
G	Forecast irradiance (W/m^2)
G_{stc}	Standard test condition irradiance (W/m^2)
i, j, k	Index variables
k_c	Relative temperature coefficient (%/°C)
$\mathcal{L}$	Load forecast dataset
L	Threshold limit for determining a sunny day
M	Number of non-zero elements in the datasets
N	Number of elements in the stored datasets
$\mathcal{P}$	PV unit dataset
P_{batt}	Power measured at the battery unit (W)
$\hat{P}_{\text{batt}}$	Battery power prediction (W)
$\hat{P}_{\text{load}}$	Load prediction (W)
P_{PV}	Power measured at the PV unit (W)
$\hat{P}_{\text{PV}}$	PV prediction (W)
$P_{\text{PV}}^{\max}$	PV system rating (W)
$P_{\text{PV-0}}^{\max}$	Uncompensated PV system rating (W)
$\hat{P}_{\text{PV-0}}$	PV prediction based on the uncompensated PV rating (W)
$P_{\text{PV-nor}}$	Normalized PV power values
$\hat{P}_{\text{PV-nor}}$	Normalized PV power prediction values
$P_{\text{PV-nz}}$	Non-zero normalized PV power values

$\hat{P}_{\text{PV-nz}}$	Non-zero normalized PV power predictions
$P_{\text{PV-peak}}$	Daily peak of PV power (W)
$\hat{P}_{\text{PV-peak}}$	Daily peak of predicted PV power (W)
RMSE_{PV}	Root-mean-square error between the prediction and actual PV power
$\text{RMSE}_{\text{PV-nz}}$	Root-mean-square error between the non-zero prediction and actual PV power
SOC	Battery state-of-charge (%)
SOC_{min}	Lower limit of the state-of-charge (%)
$\widehat{\text{SOC}}$	Predicted state-of-charge (%)
$\widehat{\text{SOC}}_0$	Uncompensated predicted SOC (%)
T	Ambient Temperature forecast (°C)
T_c	PV cell temperature (°C)
T_{noc}	Nominal operating cell temperature (°C)
T_{stc}	Standard test condition temperature (°C)
ΔSOC	Difference in SOC
$\Delta\widehat{\text{SOC}}$	Difference in SOC prediction
$\overline{\Delta\text{SOC}}$	Mean of ΔSOC
$\overline{\Delta\widehat{\text{SOC}}}$	Mean of $\Delta\widehat{\text{SOC}}$
ϵ_{b}	Battery unit fixed losses (W)
η_{b}	Efficiency of the battery unit
η_{chg}	Efficiency of the battery when charging
η_{dis}	Efficiency of the battery when discharging
η_{MPP}	Efficiency of the PV system at MPP
γ_{PV}	Compensation factor for PV system rating
γ_{batt}	Compensation factor for battery capacity
τ	Data collection interval (h)

I. INTRODUCTION

One of the fundamental objectives in microgrid operation is to maintain a balance between available power and load demand [1], so that the system frequency and voltage profile are at desirable levels. Energy management systems (EMS) often use predictions of near-term energy production and load consumption in order to make effective operational decisions to help maintain this balance in the foreseeable future [2]–[5]. In the absence of dispatchable energy sources, one may be forced to pre-emptively shed some less critical loads in order to extend the operating duration for more critical loads [6]. Hence, it is very important to have accurate predictions of potential supply and expected consumption so that the scheduling of such shedding can be performed effectively to minimize unnecessary power curtailment or service interruption.

To achieve high quality predictions, one must rely on accurate models of the key system components. In an islanded photovoltaic (PV) and battery based microgrid, as shown in Fig. 1, the models of the PV subsystem and the battery subsystem play a critical role [7], [8]. Any uncertainties in these models will lead to inaccurate predictions, and thus result in poor energy management decisions. These uncertainties can vary with time, operating conditions, and environmental factors. Thus, it is highly desirable to identify these uncertainties and correct them online in real-time [9].

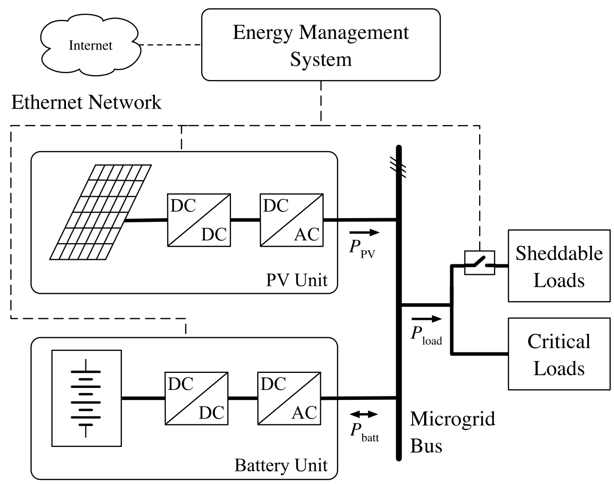

FIGURE 1. An islanded microgrid with PV and battery storage, with critical and sheddable loads.

Among all the variables, the weather forecasts and the load demand play key roles in the decision-making process [10]. The information provided by the weather forecasts (e.g. those available from Environment Canada) includes point estimates of the future irradiance and temperature levels at the PV array site. This information can be used to predict PV power production [11] by using the models of the PV array and the associated power electronic converters with the forecasted irradiance data [12]. A key parameter in the prediction model is the power rating of the PV array used. Any uncertainties there will result in either an overestimate or an underestimate of the PV power production.

A battery model is used to estimate the amount of stored energy. The accuracy of this model is also vital to ensure reliable operation of the microgrid. Even though different battery models have been developed in the literature [13]–[15], a discrete Coulomb-counting model is chosen herein to balance its accuracy and computational effectiveness for real-time implementation. This model is essentially based on calculations of the power flowing into and out of the battery. The model also takes into account the losses in the charging and discharging processes [10], [16], [17]. A key parameter of interest herein is the battery storage capacity. Any uncertainties in this parameter will result in an incorrect estimate of the available stored energy.

If such models are used in a predictive EMS, these model uncertainties will affect the quality of the energy management decisions. For example, consider the EMS in [7], where 48 hour ahead predictions are used to schedule load shedding to avert or reduce the duration of outages for critical loads. If the predictions are incorrect, then either too much or too little load will be shed. Since the microgrid operates in closed-loop, the effects of such model uncertainties may be masked, and may not be immediately noticeable. However, over a course of prolonged operation, the cumulative effects can be detrimental. If these uncertainties can be identified and corrected subsequently in real time, both the duration and the number of outages for critical loads can be reduced or eliminated.

It is important to note that the uncertainties considered here differ from the inherent deviations between the forecast and actual PV production. Such deviations have been dealt with by using model-predictive control [1], [18], robust optimization [19], [20], and stochastic optimization [17], [21]. The impact of forecast uncertainties on a demand response strategy is also explored in [22]. These forecast uncertainties are caused by the inherent stochastic nature of weather conditions, specifically clouds in the case of PV forecasting, and can therefore never be completely eliminated. The model parameter uncertainties under investigation in this work are instead relatively constant or slowly changing over a long period of time. They represent a constant source of error in the predictions, and as such are worthy of correction or compensation. By removing this persistent source of error, the overall prediction quality can be ultimately improved, independent of the variations due to forecast uncertainties. In comparison to the research on forecast uncertainties, little work has been done on dealing directly with uncertainties in the models used in the prediction process.

Among the limited work in the literature, model uncertainties are discussed and analyzed in [23], however it does not investigate any compensation techniques. Another approach to PV production estimation is presented in [24], which calculates the parameters of the nonlinear PVUSA model based on measured power, calculated clear-sky irradiance, and forecasted temperature. The impacts of the discrepancies between the actual and the predicted PV production in a grid-connected microgrid have also been considered in [25]. In this case, a compensation factor based on the ratio of the sum of the two latest consecutive actual PV measured power and the sum of the corresponding two latest consecutive predicted PV production is proposed. This compensation factor is then used to improve the PV power estimation in the model predictive control scheme. However, given that the predicted PV production based on the local weather forecast can deviate significantly from the actual power production, particularly over just the two most recent sample points, the compensation factors calculated using this approach will be sensitive to volatile changing cloud conditions, since these samples are taken every 30 minutes and can change drastically over this period. This may lead to over- or under-compensation.

In this paper, model uncertainties in the PV system rating and battery storage capacity parameters are addressed directly. A novel technique to compensate them has been developed. The technique utilizes stored daily measurements from the power electronic converters to achieve more accurate predictions of the PV production and the battery state-of-charge (SOC). For compensating uncertainties in the PV system rating parameter, the technique uses the characteristics of the daily PV profile under relatively cloud-free conditions to determine the compensation, making it less sensitive to short-term weather variations. It has been shown that the developed technique can potentially improve the accuracy of the PV production prediction by as much as 17%. It can virtually eliminate all the errors caused by an uncertain battery capacity parameter in the SOC estimate in the chosen scenarios. In combination with a pre-emptive load shedding strategy, the EMS can reduce the total outage duration for critical loads by 11% (for a modeled PV system overrating of 14% and a battery capacity overrating of 12%), without adding any additional hardware.

The paper is organized as follows: In Section II, the models for the PV rating and the battery capacity have been established and the nature of the uncertainties in these models have been analyzed. Then, potential solutions to deal with them are developed in Section III. Evaluation of these solutions has been carried out in Section IV, together with validation and verification. Finally, conclusions are drawn in Section V.

II. PREDICTION OF PV PRODUCTION AND STORED ENERGY

A. SYSTEM DESCRIPTION

Consider the islanded microgrid shown in Fig. 1, which represents a small-scale application such as on top of a building or a remote monitoring station. The PV unit contains a PV array (made up of panels of similar type and rating), a dc-dc converter with a maximum power-point tracking (MPPT) algorithm, and a 3-phase inverter. The energy storage unit includes a battery bank, a bidirectional dc-dc converter, and a 3-phase inverter. The loads can be divided into critical and non-critical groups. The critical loads should be served with the highest priority, while the non-critical ones may be shed if necessary to preserve energy for the former. The EMS relies on 48-hour ahead forecasts of solar irradiance and ambient temperature from an external provider, and the prediction of the load consumption profile is based on historical data. The EMS then predicts the battery SOC in order to assess potential energy shortages or oversupply. This information is used to make pre-emptive decisions to shed a portion of the non-critical loads. The details, implementation, and benefits of this strategy have been described in [7]. However, it was assumed that there were no uncertainties in the PV models, nor in the battery models, which was an ideal case. The focus of the current investigation is to deal with uncertainties in these models so that more accurate predictions can be made. The proposed approach is a data driven compensation technique.

B. DATA SEQUENCES

Assume that the measurements from the PV and battery units are represented as data sequences sampled at an interval of τ. For the PV unit, the dataset is represented by $\mathcal{P}$:

$$\mathcal{P} = \{P_{\mathrm{PV}}[k] \mid k = 0, \ldots, N-1\} \tag{1}$$

where P_{PV} is the measured power in Watts (W) and N is the size of the sequence.

The battery unit dataset can be represented by $\mathcal{B}$:

$$\mathcal{B} = \{P_{\text{batt}}[k], \text{SOC}[k] \mid k = 0, \ldots, N-1\} \tag{2}$$

where P_{batt} is the measured power in W flowing into or out of the battery, and SOC is the state-of-charge which can be obtained from the battery converter.

For the forecast irradiance, the interpolated irradiance is represented by $\mathcal{F}$

$$\mathcal{F} = \{(G[k], T[k]) \mid k = 0, \ldots, N-1\} \tag{3}$$

where G and T are the forecast irradiance in W/m^2 and temperature in °C, respectively.

Finally, a load forecast is represented by $\mathcal{L}$

$$\mathcal{L} = \{\hat{P}_{\text{load}}[k] \mid k = 0, \ldots, N-1\} \tag{4}$$

where $\hat{P}_{\text{load}}$ is the forecast load in W.

C. PV AND BATTERY MODELS

1) PV PREDICTION MODEL

The predicted PV power output at sample k, $\hat{P}_{\text{PV}}[k]$, can be obtained by using the irradiance forecast relationship as follows [26]. First, the PV cell temperature T_c is estimated based on the forecast irradiance and ambient temperature using the following characteristic relations [27]

$$T_c = T[k] + \frac{G[k]}{800}(T_{\text{noc}} - 20) \tag{5}$$

where T_{noc} is the nominal operating cell temperature of 44.2 °C. The power output can then be calculated from

$$\hat{P}_{\text{PV}}[k] = \frac{G[k]}{G_{\text{stc}}} P_{\text{PV}}^{\max}(1 + k_c(T_c - T_{\text{stc}})\eta_{\text{MPP}} \tag{6}$$

where $G_{\text{stc}} = 1000$ W/m^2, $k_c = -0.430$ %/°C [28], $T_{\text{stc}} = 25$ °C, and η_{MPP} is the efficiency of the PV unit at the maximum power point.

2) BATTERY PREDICTION MODEL

Any difference between the PV generation and the load demand must be balanced by the battery through supply ($\hat{P}_{\text{batt}} > 0$) or absorption ($\hat{P}_{\text{batt}} < 0$). Hence, the battery power can be expressed as

$$\hat{P}_{\text{batt}}[k] = \hat{P}_{\text{load}}[k] - \hat{P}_{\text{PV}}[k]. \tag{7}$$

The relationship between the predicted stored energy, represented as a percentage of the total battery capacity, and the charging/discharging power can be represented with an accumulation equation

$$\widehat{\text{SOC}}[k] = \widehat{\text{SOC}}[k-1] - \frac{100\%}{E_{\text{batt}}^{\max}}(\hat{P}_{\text{batt}}[k] - \epsilon_{\text{b}})\tau\eta_{\text{b}}(\hat{P}_{\text{batt}}[k]). \tag{8}$$

where $\text{SOC}[k]$ is the predicted energy in the battery at k, and ϵ_{b} and $\eta_{\text{b}}(\hat{P}_{\text{batt}}[k])$ are parameters that account for the losses and the efficiency of the battery charging/discharging systems, respectively. The efficiency is a function of the power direction

$$\eta_{\text{b}}(\hat{P}_{\text{batt}}[k]) = \begin{cases} \eta_{\text{chg}}, & \hat{P}_{\text{batt}}[k] \leq 0 \\ \dfrac{1}{\eta_{\text{dis}}}, & \hat{P}_{\text{batt}}[k] > 0 \end{cases}. \tag{9}$$

where η_{dis} is the discharge efficiency and η_{chg} is the charge efficiency.

Furthermore, the battery capacity limits are bounded by the following constraint

$$\text{SOC}_{\min} \leq \widehat{\text{SOC}}[k] \leq 100\% \tag{10}$$

where $\text{SOC}_{\min}$ is the minimum charge level of the battery. At times when there is insufficient PV production to meet the load, and if the stored energy drops below this limit, the microgrid will have to shut down.

D. MODEL UNCERTAINTIES

1) UNCERTAINTIES IN THE PV RATING PARAMETER

For the microgrid in Fig. 1, it is assumed that the maximal PV rating is $P_{\text{PV-0}}^{\max}$. However, in practice, the PV array seldom achieves this ideal level of performance. This can be due to mistakes during commissioning, PV array degradation, or an accumulation of contaminants on the panels, just to mention a few. Thus, using this value blindly to predict the PV production can lead to errors. Since the PV rating does not change dynamically with other system variables, it is reasonable to assume that the true value, $P_{\text{PV}}^{\max}$, is related to $P_{\text{PV-0}}^{\max}$ in a linear fashion, and that there is no offset error:

$$P_{\text{PV}}^{\max} = \gamma_{\text{PV}} P_{\text{PV-0}}^{\max} \tag{11}$$

where γ_{PV} represents the scaling factor between the presumed rated PV power production and the actual maximal production, and is known as the PV compensation factor.

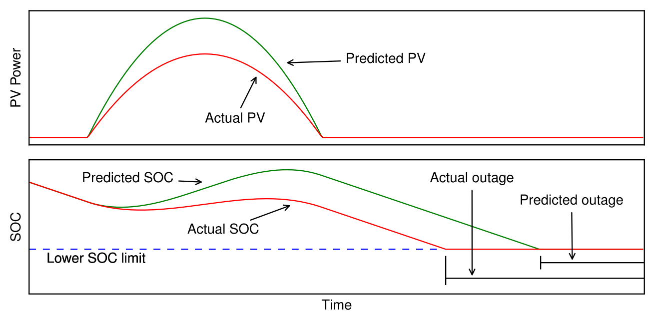

FIGURE 2. Effect of parameter uncertainties in the PV rating. The over-prediction of PV production leads to an over-prediction of the SOC, and thus an incorrect outage prediction.

To illustrate the effect of this uncertainty on the performance of a microgrid, consider a case where the PV system rating has been overrated. This will lead to overconfidence in estimating the amount of PV production, which could result in an earlier than expected outage as shown conceptually in Fig. 2. This error in prediction of the PV production has led to a significantly higher SOC estimate. The actual energy reserve in the microgrid is considerably lower than expected, which would lead to unplanned outages due to shortages of energy.

2) UNCERTAINTIES IN THE BATTERY CAPACITY PARAMETER

For the battery, the presumed capacity is represented as $E^{max}_{batt\text{-}0}$. Uncertainties in this parameter, potentially due to incorrect system characterization or aging, can also lead to incorrect prediction of the amount of stored energy in the battery. The actual value E^{max}_{batt} could only be a fraction of the rated battery capacity $E^{max}_{batt\text{-}0}$:

$$E^{max}_{batt} = \gamma_{batt} E^{max}_{batt\text{-}0} \tag{12}$$

where γ_{batt} represents the scaling factor for the battery capacity parameter, and is known as the battery compensation factor.

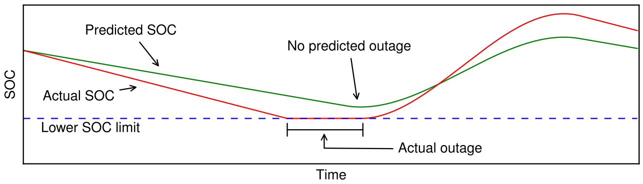

FIGURE 3. Effect of parameter uncertainty in the battery capacity. The over-estimate of the battery capacity results in a missed prediction of an outage.

The effect of such an error can be observed in Fig. 3, where an uncertainty has led to an inaccurate estimate of the SOC, which can then result in an unexpected system shutdown. The outage could have been averted by pre-emptive shedding of non-critical loads, if an accurate prediction had been available.

Clearly, it is vital to have actual models to represent the true status of the PV rating and battery capacity. Hence, the main focus of this paper is to develop techniques to identify such uncertainties and effectively compensate them to prolong the operating duration for critical loads.

E. PROBLEM STATEMENT

The objectives of the current investigation are (1) to use the measurement data sequences $\mathcal{P}$, $\mathcal{B}$, and the forecast $\mathcal{F}$ to detect model uncertainties, and (2) to accurately determine the compensation factors γ_{PV} and γ_{batt} for P^{max}_{PV} and E^{max}_{batt}, respectively, so that the PV production prediction, $\hat{P}_{PV}$, and the stored energy prediction, $\widehat{SOC}$, are closer to the actual values, i.e.,

$$\left\| P_{PV} - \hat{P}_{PV} \right\| < \left\| P_{PV} - \hat{P}_{PV\text{-}0} \right\| \tag{13}$$

and

$$\left\| SOC - \widehat{SOC} \right\| < \left\| SOC - \widehat{SOC}_0 \right\| \tag{14}$$

The above tasks are carried out by using only the measurements from the converters and the forecasts, without installing any additional sensors, so that this technique can be easily retrofitted into existing systems. The effectiveness of the compensation techniques will also be demonstrated in Section IV by showing the extension of the duration for critical load support when these compensated models are incorporated in a pre-emptive load shedding energy management strategy.

III. DETERMINATION OF THE COMPENSATION FACTORS

A. COMPENSATION FACTOR FOR PV RATING

The key approach for determining the correct γ_{PV} in (11) is to compare the actual measured PV power production against the predicted production under a clear-sky condition.

In the absence of clouds, the PV production will closely follow the rise and set of the sun, with a peak at approximately mid-day. Under these conditions, one can simply take just the peak values in the measured data sequences and compare them with the predicted values to calculate the compensation factor. However, when clouds are present, this approach is complicated by the variability of the PV power production. Comparing the peaks on a cloudy day is unlikely to result in an accurate compensation factor. Therefore, if one can identify relatively cloud-free days, where the forecast PV profile is similar to the actual PV profile, these days can be used as references to calculate the compensation factor.

To determine whether a given day is relatively cloud-free, the root-mean-squared error between P_{PV} and $\hat{P}_{PV}$ can be used

$$\mathrm{RMSE}_{PV} = \sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} (P_{PV}[i] - \hat{P}_{PV}[i])^2} \tag{15}$$

where, for an ideal day with a correct value for γ_{PV}, the resulting RMSE_{PV} would be very small, or even near zero, indicating an accurate prediction. However, given that γ_{PV} is unknown, the datasets must be normalized first. Also, the overnight periods and any outages that have occurred during the considered interval should be removed before (15) can be applied. Therefore, the resulting solution is separated into four steps: data normalization, removal of overnight and outage periods, determination of cloud-free conditions, and calculation of the PV compensation factor.

1) DATA NORMALIZATION

First, the peaks of the actual PV measurements and the PV prediction datasets are determined: $P_{PV\text{-}peak} = \max_{i=0}^{N-1} P_{PV}[i]$ and $\hat{P}_{PV\text{-}peak} = \max_{i=0}^{N-1} \hat{P}_{PV}[i]$, where i indexes the N stored data points from the previous day. These peak values are used for both normalization and for determining the PV compensation factor later on.

The datasets are then normalized as follows

$$P_{PV\text{-}nor}[i] = 100 \frac{P_{PV}[i]}{P_{PV\text{-}peak}}, \quad i = 0, \ldots, N-1 \tag{16}$$

$$\hat{P}_{PV\text{-}nor}[i] = 100 \frac{\hat{P}_{PV}[i]}{\hat{P}_{PV\text{-}peak}}, \quad i = 0, \ldots, N-1 \tag{17}$$

where $P_{\text{PV-nor}}$ and $\hat{P}_{\text{PV-nor}}$ are the normalized datasets containing the actual measured PV power production and the forecast PV power predictions, respectively.

2) REMOVAL OF OUTAGE AND OVERNIGHT PERIODS

An additional challenge is that the actual recorded PV production will also include the effects of control actions such as shutdowns, but these actions will not appear in the prediction. Subsets of the data that contain just the non-zero PV production periods are thus used to calculate the comparison, where $P_{\text{PV-nz}}$ and $\hat{P}_{\text{PV-nz}}$ are the non-zero data points of normalized PV power measurements and the predicted PV power production, respectively, and M is the number of non-zero data points.

3) DETERMINATION OF CLOUD-FREE CONDITIONS

The root-mean-squared error can now be found using (15), after substituting $P_{\text{PV-nz}}$ for P_{PV}, $\hat{P}_{\text{PV-nz}}$ for $\hat{P}_{\text{PV}}$, and M for N

$$\text{RMSE}_{\text{PV-nz}} = \sqrt{\frac{1}{M-1}\sum_{i=0}^{M-1}(P_{\text{PV-nz}}[i] - \hat{P}_{\text{PV-nz}}[i])^2} \quad (18)$$

If the $\text{RMSE}_{\text{PV-nz}}$ value is less than a certain threshold L, the agreement is deemed to be acceptable, suggesting that the chosen day is relatively cloud-free. A threshold value L of 10% effectively discriminates between sunny and cloudy days, approximately corresponding with the metrological criteria separating a "sunny" forecast from a "mostly sunny" one [29].

4) CALCULATION OF THE PV COMPENSATION FACTOR

Given that the chosen day has been identified as relatively cloud-free, the PV compensation factor can now be calculated as

$$\gamma_{\text{PV}} = \frac{P_{\text{PV-peak}}}{\hat{P}_{\text{PV-peak}}} \quad (19)$$

B. COMPENSATION FACTOR FOR SOC ESTIMATION

The compensation factor for the battery storage capacity γ_{batt} in (12) can be found by comparing the calculated SOC using the battery model and the measured P_{batt} values, against the recorded SOC values. First, one can use (8) to determine the profile of the $\widehat{\text{SOC}}$ by iterating over P_{batt}, starting from the initial value $\widehat{\text{SOC}}[0] = \text{SOC}[0]$.

Next, the differences between subsequent data points in the datasets can be calculated as

$$\Delta\text{SOC}[i] = \text{SOC}[i+1] - \text{SOC}[i], \quad i = 0, \ldots, N-2 \quad (20)$$

$$\Delta\widehat{\text{SOC}}[i] = \widehat{\text{SOC}}[i+1] - \widehat{\text{SOC}}[i], \quad i = 0, \ldots, N-2 \quad (21)$$

Note that from (8), $\Delta\widehat{\text{SOC}}[i]$ is proportional to $1/E^{\max}_{\text{batt-0}}$, and $\Delta\text{SOC}[i]$ is also proportional to $1/E^{\max}_{\text{batt}}$, since it is calculated from the SOC estimated at the battery converter. Therefore, from (12), it can be assumed that

$$\Delta\widehat{\text{SOC}} = \gamma_{\text{batt}}\Delta\text{SOC} \quad (22)$$

A linear regression between $\Delta\widehat{\text{SOC}}$ and ΔSOC can then be used to determine the battery compensation factor as

$$\gamma_{\text{batt}} = \frac{\sum_{i=0}^{N-2}(\Delta\text{SOC}[i] - \overline{\Delta\text{SOC}})(\Delta\widehat{\text{SOC}}[i] - \overline{\Delta\widehat{\text{SOC}}})}{\sum_{i=0}^{N-2}(\Delta\text{SOC}[i] - \overline{\Delta\text{SOC}})^2} \quad (23)$$

where $\overline{\Delta\widehat{\text{SOC}}}$ is the mean of the $\Delta\widehat{\text{SOC}}$ dataset, and $\overline{\Delta\text{SOC}}$ is the mean of the ΔSOC dataset.

It should be emphasized that the calculation of the SOC compensation factor is a backward-looking technique which operates on data recorded from the previous day. It is, therefore, not affected by uncertainties in the PV production or load forecast. Also, note that this technique does not interact with the PV compensation approach from the previous subsection.

IV. VALIDATION OF THE COMPENSATION TECHNIQUES

The developed uncertainties compensation techniques have been implemented on a simulated microgrid and EMS in Python with SciPy [30]. The key properties, such as PV curtailment and low-SOC shutdown have also been implemented. The data used are a 42-day irradiance and temperature dataset recorded from a rooftop system with a Kipp & Zonen SP Lite2 pyranometer and an Analog Devices TMP35 temperature sensor. This data is processed with the PV model to create the PV production profile used for the simulation. The corresponding forecast data for the same location is obtained from the Environment Canada Global Environmental Multiscale numerical weather prediction model, specifically the High Resolution Deterministic Prediction System dataset [31]. This forecast offers a maximum horizon of 48 hours, and is updated every six hours as new information becomes available. The load is represented by an aggregated daily residential load profile. The inputs from the simulated power electronic converters are sampled once every 2 minutes, and the EMS functions are executed at 4 minute intervals to carry out PV power production and battery stored energy predictions, and make corresponding load-shedding decisions [7]. A one-day rolling history for data from $\mathcal{P}$, $\mathcal{B}$, and $\mathcal{F}$ are stored in this case for analysis, which includes a daily peak for data normalization purposes.

To validate the techniques, errors are deliberately introduced into the EMS prediction model parameters so that they differ from those in the models used in the PV and battery subsystems of the simulated microgrid. The PV rating is overrated by 14%, and the battery capacity is overrated by 12%. These uncertainties represent possible practical scenarios such as incorrect parameter configuration during installation, or PV panel soiling and battery aging. The results produced with these parameter uncertainties are then compared with those produced with the true parameters. Finally, the compensation technique is enabled to demonstrate the effectiveness of the approach.

A. IMPROVEMENT IN PV PRODUCTION PREDICTIONS

The effect of the compensation technique on the prediction of the PV production can be observed in Fig. 4. The original predicted PV production is denoted $\hat{P}_{\text{PV-0}}$. Thanks to the compensation factor, as can be seen, the compensated prediction matches the actual PV generation much more closely than the original prediction.

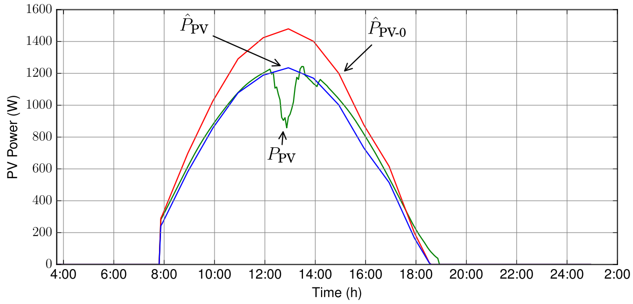

FIGURE 4. **The original PV prediction, the compensated PV prediction, and the measured PV power.**

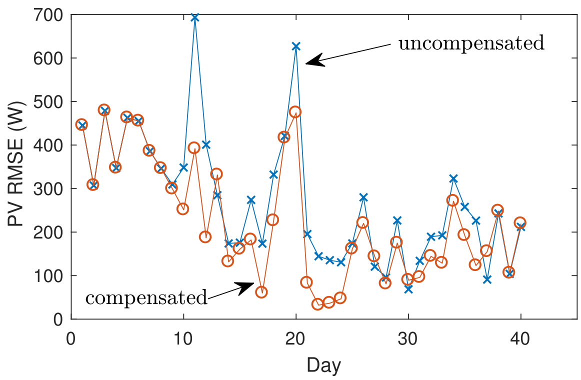

FIGURE 5. **Daily PV actual vs. forecast RMSE, with and without uncertainty compensation.**

To evaluate the overall improvement with the proposed approach, the difference between the actual and predicted PV productions based on the forecast is determined on a daily basis for a period of 42 days. The resulting RMSE values are shown in Fig. 5.

It is interesting to note that, for the initial nine days no compensation was carried out, since they were mostly cloudy days. None of them can be used as the reference for determining the compensation factors. On the tenth day, a near full-sun irradiance day has been detected and subsequently used for the PV compensation factor calculation. Hence, the accuracy of the PV production prediction has been improved significantly. Over a period of 42 days, the average daily improvement in terms of RMSE is about 17%.

B. IMPROVEMENT IN SOC PREDICTIONS

To evaluate the effectiveness of the proposed technique on SOC prediction, the predicted SOCs with and without compensation for a period of one day are shown in Fig. 6. The original prediction is labeled as $\widehat{\text{SOC}}_0$. It can be seen that the compensation technique is able to virtually eliminate the error caused by the battery capacity parameter uncertainty for the previously recorded day's dataset, where the actual PV production and load behaviour are already known. It is important to note that the technique cannot eliminate the error between the future predicted SOC and the actual SOC, as that would require perfect knowledge of the future PV production and loads. The technique instead ensures that the SOC prediction model is as accurate as possible, with respect to the battery capacity parameter, based on the known data. Hence, the accuracy of future SOC predictions can be improved.

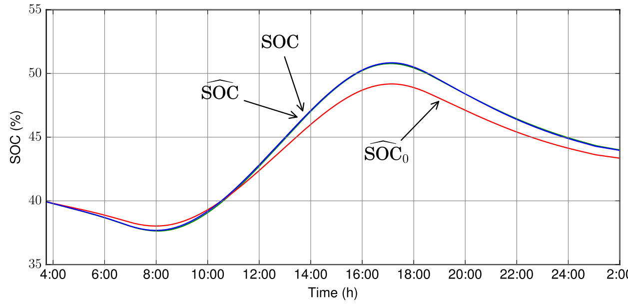

FIGURE 6. **The original SOC prediction, the compensated SOC prediction, and the recorded SOC. Note that the compensated SOC prediction overlays the recorded SOC.**

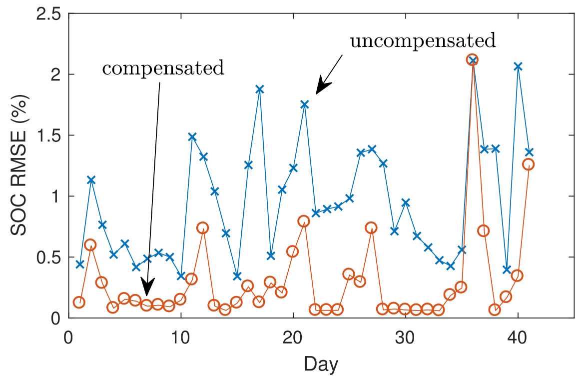

FIGURE 7. **The RMSE between the actual and predicted SOCs with and without compensation.**

The daily RMSE values for the SOC predictions with and without compensation are presented in Fig. 7. It can be seen that the compensation improves the performance of the SOC predictions.

C. IMPROVEMENT IN OUTAGE REDUCTION

The ultimate objective of the developed compensation techniques is to obtain more accurate predictions of PV production and the SOC so that the EMS can make more effective decisions in the planning of load shedding actions to minimize both the number and the duration of any outages. To demonstrate this point, three case studies have been performed for the same duration of 42 days, but with various levels of parameter uncertainties and their compensation scenarios. In addition, without loss of generality, a Gaussian load variation profile is introduced so that the load forecast does not instantaneously match the simulated load.

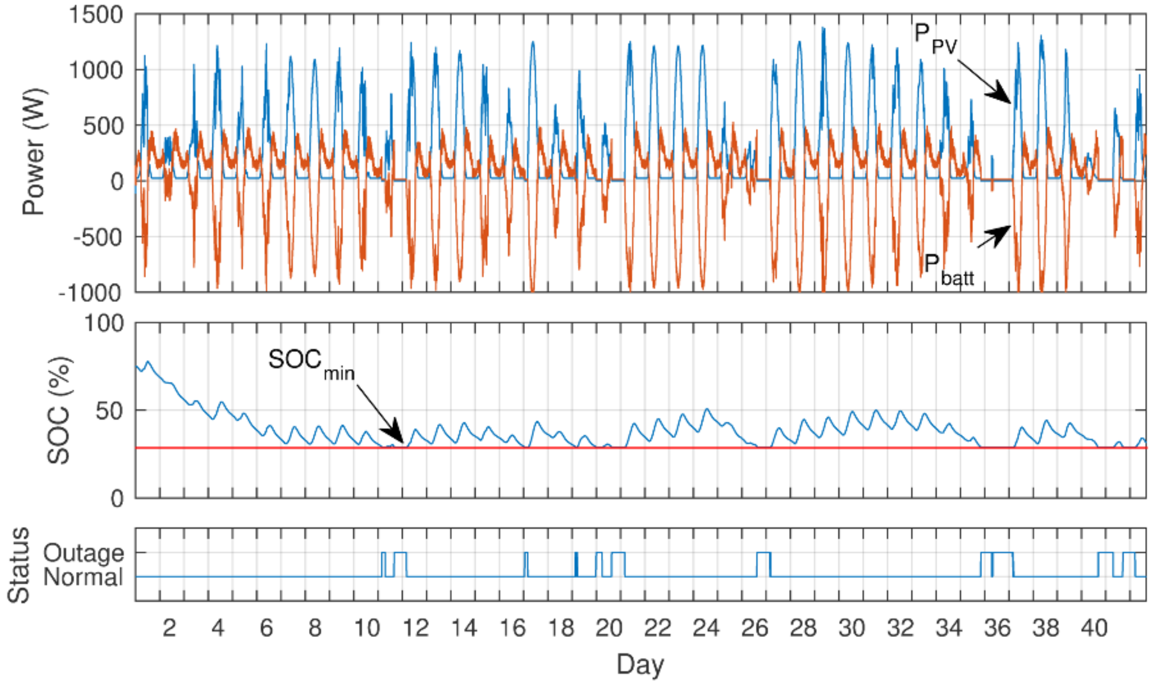

FIGURE 8. The outage performance of the microgrid over 42 days with model parameter uncertainties. (Scenario 1).

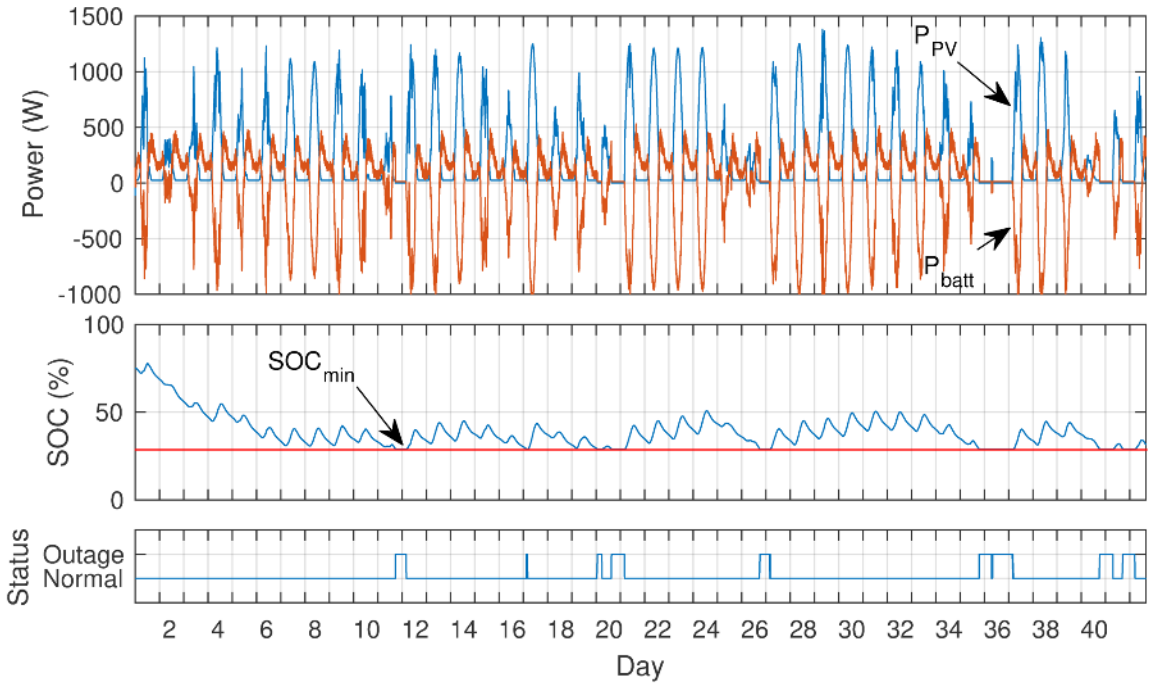

FIGURE 9. The outage performance of the microgrid with the developed uncertainty compensation scheme. (Scenario 2).

In the first scenario, intentional uncertainties are introduced into the prediction model parameters, with the PV system rating being overrated by 14% and the battery capacity being overrated by 12%. The corresponding results are shown in Fig. 8. There are 20 outages with a total duration of 110 hours.

The second scenario employs the uncertainty compensation scheme developed in Section III, with the same introduced prediction model parameter uncertainties. The results are shown in Fig. 9. As can be seen, the microgrid has experienced 16 outages in total, of collectively 98 hours in duration. This is an 11% reduction in the overall outage duration achieved simply by using the proposed scheme without any additional hardware devices.

In the third scenario, it is assumed that the exact parameters are used in the prediction process. Therefore, the EMS always makes the correct decisions. Due to space limitations, the results from this scenario is not included herein, however the results are very similar to those in the second scenario. The microgrid has experienced 15 outages totalling 98 hours, which represents the best possible case. This illustrates that the developed technique can almost achieve the same level of performance as if there were no model uncertainties.

As a comparison, in an identical operating environment, if no pre-emptive load-shedding EMS scheme had been used, there would have been 35 outages totalling 205 hours. The results of the above studies are summarized in Table 1. These results have demonstrated the effectiveness the developed scheme used with the pre-emptive load shedding strategy.

TABLE 1. Summary of results over a 42-day interval.

Scenario	Outages	Totale Outage Time
EMS with Uncertainties	20	110 hours
EMS with Compensated Parameters	16	98 hours
EMS with Exact Parameters (best case)	15	98 hours
No Predictive EMS (worst case)	35	205 hours

V. CONCLUSIONS

A method for compensating uncertainties in PV rating and battery capacity model parameters in a predictive energy management system for islanded microgrids has been developed in this work. The technique uses measurements provided by the inverters, along with weather forecast data, to improve the accuracy of the models used for predictions, which are then used to make outage mitigation decisions. No additional sensors are needed to implement the technique, and the algorithms are computationally efficient to be embedded in an existing EMS. The technique has been implemented and validated within a simulated pre-emptive load shedding EMS for an islanded PV and battery microgrid. The results have shown that formerly declared outages attributable to model uncertainties can be almost completely eliminated. As a result, for a modeled PV system overrating of 14% and a battery capacity overrating of 12%, an 11% improvement in the reduction of overall outage duration has been achieved.

ACKNOWLEDGMENT

The authors would like to express their gratitude to the Natural Sciences and Engineering Research Council (NSERC) of Canada for providing support for this work through a Discovery Grant.

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