Distributed Stochastic Control of Microgrids
Based on PV Power Predictions

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Abstract

This paper considers the distributed power management of a microgrid consisting of consumers, PV generators, and batteries. The objectives of the microgrid management are (1) the supply-demand balancing, (2) the low dependency on the main grid based on the local-production-local-consumption policy, and (3) the reservation of battery charges to prepare for faults or islanded operations. For the microgrid management, it is important to explicitly take account of the prediction of PV power generation because it heavily depends on weather conditions. By extending the result due to Takeda and Takaba (Trans. SICE, vol. 54, no. 2, 2018), we propose a distributed stochastic model predictive control method using the predicted PV powers. In the proposed method, each battery management system (BMS) attached to a battery determines the power flows from and into the battery in a distributed manner so that the above objectives are achieved in the local area around the BMS. We verify the effectiveness of the proposed method by numerical simulations.

1 Introduction

Under the assumption of mass introduction of photovoltaic (PV) generators in the near future, this paper considers the distributed power management of a microgrid consisting of a number of PV’s, batteries, consumers, etc. The objective of the microgrid management is to keep stable energy supply with low dependency on the main grid based on the local-production-local-consumption policy. For this purpose, it is important to control the power flows in the microgrid by using the future information of the PV generations. One of the major difficulties is that the power generated by the PV’s contains large uncertainties depending on weather conditions. An approach based on the stochastic model predictive control (SMPC) has recently been proposed to cope with these uncertainties for the simplified microgrid model in which PV’s, batteries, and consumers are lumped into single agents [1, 2]. In particular, Takeda and Takaba combine the SMPC with the Just-In-Time (JIT)-based PV power prediction in order to deal with practical PV power profiles [2].

In this paper, by extending the results in [2], we will propose a distributed SMPC method with the JIT-based PV power prediction for a more realistic microgrid model in which PV’s, batteries, and consumers are distributed over the power grid. Each battery management system (BMS) controls the power flows of the corresponding battery to optimize its local objectives in the receding horizon control manner. Cooperation among the BMSs will be implemented through the exchange of predicted control sequences.

This paper is organized as follows. In Section 2, we will briefly review the PV power prediction method based on the Just-In-Time technique [3]. In Section 3, we formulate the stochastic model predictive control problem for the distributed microgrid model, and solve the problem with the aid of the randomized convex optimization technique. We will verify the effectiveness of the proposed method by a numerical simulation in Section 4. Section 5 is the conclusion.

2 PV Power Prediction

For the purpose of stable power grid management, we need to predict future supplies from renewable energies, in particular, PV's in this paper. As is mentioned in Section 1, the prediction of PV power supplies is difficult since they are heavily dependent on weather conditions. The Just-In-Time (JIT) modeling method is known as one of the effective methods to cope with this difficulty [3]. In this section, we will review the prediction method of PV power supplies based on the JIT modeling technique [2, 3]. The JIT-based PV prediction consists of two steps: the solar irradiance prediction and the conversion of the solar irradiance to the PV power generation.

2.1 Solar irradiance prediction based on JIT modeling

By the JIT modeling technique, we can obtain the one-day-ahead prediction of solar irradiance of the day based on the database consisting of past weather forecast data.

The schematic diagram of the JIT modeling is depicted in Fig. 1.

In the standard modeling on the right side of Fig. 1, a global model is constructed by using all input/output
datasets. We predict the output by directly injecting a given input data to the obtained model.

On the other hand, in the JIT modeling, we select a small number of datasets from a database which stores past input-output data. The output for a given input data is estimated from the obtained datasets based on the idea that outputs for close inputs are close.

The procedure of the JIT-based one-day-ahead solar irradiance prediction is described as follows. We first prepare the database that stores past weather forecast and solar irradiance data as input and output data, respectively. Then, we carry out the following steps at 0:00 on the day to predict the 24 hour sequence of solar irradiance.

1) Obtain the weather forecast data of the day as the input.
2) Select from the database a small number of datasets whose input data are close to the above forecast data.
3) Estimate the one day solar irradiance on the day by weighted averaging the past solar irradiances of the selected datasets.

The database for the JIT-based solar irradiance prediction consists of MSM-GPV (Meso-Scale Model Grid Point Value) data from the Japan Meteorological Business Support Center (JMBSC) [4] and the past solar irradiance measurements from the Japan Meteorological Agency (JMA) [5]. The MSM-GPV is a numerical forecast model which predicts the meteorological factors every 5 km for 39 hours. The forecast data is updated every 3 hours, i.e. eight times a day. The meteorological factors in the database are atmospheric pressure, wind (South-North/East-West), temperature, humidity, rainfall, cloudiness (high/middle/low).

The input data in the database are composed of 24 hour sequences (0:00-23:00) of 11 parameters which include the above nine meteorological factors plus the sun altitude and day length computed from the geographic coordinates of the point of interest (Table 1). The output data is the measured solar irradiance on the horizontal surface. The j-th input and output data are denoted by $x^j(h)$ and $y^j(h)$ ($h = 0, 1, \ldots, 23$), respectively. See (1) for the detail on the entries of $x^j$.

\[
x^j(h) = \begin{bmatrix}
x_1^j(h) \\
x_2^j(h) \\
x_3^j(h) \\
x_4^j(h) \\
x_5^j(h) \\
x_6^j(h) \\
x_7^j(h) \\
x_8^j(h) \\
x_9^j(h) \\
x_{10}^j(h) \\
x_{11}^j(h)
\end{bmatrix} = 
\begin{bmatrix}
DL^j(h) \\
SA^j(h) \\
Atm^j(h) \\
Tem^j(h) \\
Wew^j(h) \\
Wsn^j(h) \\
Hum^j(h) \\
MC^j(h) \\
UC^j(h) \\
RF^j(h)
\end{bmatrix}
\] (1)

At the step 2) in the solar irradiance prediction, we employ the K-Nearest Neighbors (K-NN) method to select appropriate neighborhood datasets from the database. In this method, we evaluate the closeness of the past input and output data as input and output data, respectively. See (1) for the detail on the entries of $x^j$.

\[
d_j = \sum_{h=0}^{23} \sum_{k=1}^{11} w_k |x_k^j(h) - x_k^j(h)|^2,
\] (2)

where $w_k$ ($k = 1, \ldots, 11$) are the weights which represent the relevance between each meteorological factor and the solar irradiance. Recall that, in the same way as (1), $x_k^j(h)$ represents the k-th element of the input data $x^j(h)$. In this paper, we employ the partial regression coefficients from the multiple regression analysis with solar irradiance as the objective variable and meteorological factors as explanatory variables as weights. In addition, the parameter reduction based on the Akaike Information Criterion (AIC) [6] may be employed for obtaining the minimum number of the meteorological factors which account for the solar irradiance of the point of interest.

Let $j_1, j_2, \ldots, j_K$ be the indices of the K neighborhood datasets such that $d_{j_1} \leq d_{j_2} \leq \cdots \leq d_{j_K}$. At the step 3) after the selection of the neighborhood datasets, we compute the prediction of the solar irradiance $y_{\text{JIT}}$.
by the linearly weighted average of the output data in the neighborhood datasets as
\[ y_{\text{HT}} = \sum_{k=1}^{K} a_{jk} y^{h_k}, \quad a_{jk} = \frac{w_{\text{LWA}}^{1/j}}{\sum_{l=1}^{K} w_{\text{LWA}}^{1/j}}, \] (3)
where \( w_{\text{LWA}} \) is given by the tri-cube function
\[ w_{\text{LWA}}^{1/j} = \left( 1 - \left( \frac{d_{jk}}{d_{jK}} \right)^3 \right). \] (4)

Notice that, the \( y_{\text{HT}} \) is the one-day-ahead prediction of the solar irradiance, and hence its prediction accuracy may be degraded by weather variations for the day. To improve the accuracy of the JIT-based prediction, we will add some correction to the prediction \( y_{\text{HT}} \) based on the current measurement of the solar irradiance. Let \( y \) be the true solar irradiance, and define
\[ \Delta y = y - y_{\text{HT}}. \] (5)

Since \( \Delta y \) has time correlation as can be seen from Fig. 3, we assume that \( \Delta y \) is modeled by the auto-regressive (AR) process
\[ \Delta y(t) = a_1 \Delta y(t-1) + a_2 \Delta y(t-2) + \cdots + a_T \Delta y(t-\tau) + w(t), \] (6)
where \( a_1, a_2, \ldots, a_T \) are the regression coefficients, and \( w \) is the zero mean Gaussian white noise process [2]. It may be noted that, many previous works on stochastic microgrid control (see e.g. [1]) have been reported under the assumption that the prediction errors \( \Delta y \) of the solar irradiance are Gaussian white noise processes. In addition, though the references [7, 8] derived the confidence intervals of the JIT-based solar irradiance prediction, no prediction error model useful for the stochastic microgrid control has been provided.

The regression coefficients \( a_1, \ldots, a_T \) are identified by the least squares (LS) method using the neighborhood datasets of the K-NN method.
\[
(a_1, \ldots, a_T) = \arg\min \sum_{k=1}^{K^{\text{AR}}} \sum_{h=0}^{3} \left\{ (y^{h_k} - y^{\text{HT}}(h)) \right. \\
\left. - \sum_{l=1}^{\tau} a_l (y^{h_k}(h - l) - y^{\text{HT}}(h - l)) \right\}^2, \] (7)
where \( K^{\text{AR}} \) is the number of neighborhood datasets used for the parameter estimation. To achieve good prediction accuracy, we construct the AR model from only \( K^{\text{AR}} \) neighborhood datasets. To guarantee the existence of unique LS estimates of the regression coefficients, the data matrix made up of the \( K^{\text{AR}} \) neighborhood datasets must be of full rank. If this constraint is not satisfied for any \( K^{\text{AR}} \leq K \), the lag \( \tau \) of the AR model needs to be made smaller. However, such a situation hardly happens if the number of datasets in the database and \( K \) are sufficiently large.

Let \( \hat{y}(t+k|t) \) denote the \( k \)-step prediction of \( y(t) \) based on the measurement up to time \( t \). Then, we get
\[
\hat{y}(t+k|t) = y_{\text{HT}}(t+k) + \Delta \hat{y}(t+k|t) \] (8)
and \( \Delta \hat{y}(t+k|t) \) is given by
\[
\Delta \hat{y}(t+k|t) = a_1 \Delta \hat{y}(t+k-1|t) + a_2 \Delta \hat{y}(t+k-2|t) + \cdots + a_T \Delta \hat{y}(t+k-\tau|t) \]
\[(k = 0, 1, 2, \ldots, N), \] (9)
where the initial condition is set by the solar irradiance measurements as
\[ \Delta \hat{y}(t-\tau|t) = \Delta y(t-\tau|t) = y(t-\tau|t) - y_{\text{HT}}(t-\tau|t), \]
\[(l = 1, 2, \ldots, \tau). \] (10)

Note also that the length \( N \) of the prediction interval corresponds to the control horizon in the model predictive control described later.

### 2.2 PV power prediction

To obtain the PV power prediction, it is necessary to convert solar irradiance on the horizontal surface to that on the PV panel surface. We approximate the relationship between horizontal solar irradiance and PV power generation by the following equation. It is known that a simple linearized model of the conversion from the horizontal surface solar irradiance \( y \) to the PV generation \( S \) is given by the following equation [9].
\[ S = W_{\text{nmo}} \cdot \alpha \cdot y_{\text{PV}} = \alpha \cdot y, \] (11)
where \( W_{\text{nmo}} \) and \( \alpha \) are the nominal maximal output and the performance ratio of the PV panel, respectively. \( \alpha \) is the conversion coefficient from the solar irradiance on horizontal surface to that on the PV panel surface. It follows from (5) and (11) that
\[ S(t) = S_{\text{HT}}(t) + \Delta S(t), \] (12)
\[ S_{\text{HT}}(t) = (W_{\text{nmo}} \cdot \alpha) \cdot y_{\text{HT}}(t), \] (13)
\[ \Delta S(t) = (W_{\text{nmo}} \cdot \alpha) \cdot \Delta y(t). \] (14)

Under the assumption that \( W_{\text{nmo}}, \alpha \) are exactly known, the prediction \( \hat{S} \) of the PV power generation is obtained by
\[ \hat{S}(t+k|t) = S_{\text{HT}}(t+k) + \Delta \hat{S}(t+k|t), \] (15)
where \( \Delta \hat{S}(t+k|t) = (W_{\text{nmo}} \cdot \alpha) \cdot \Delta y(t+k), \) and \( \Delta \hat{y} \) is given by (9),(10).

In the next section, we will present a distributed method for microgrid management using this PV power prediction, based on the stochastic model predictive control methodology.
3 Distributed SMPC of Microgrid

3.1 Microgrid model

The microgrid is a small- or middle-scale power grid consisting of consumers (demands), renewable energies, batteries, etc., which is connected to the main grid at one point. Throughout this paper, we will consider PV’s for the renewable energies. Fig. 2 illustrates an example of the microgrids.

The objectives of the microgrid management are

- Supply-demand balancing
- Reservation of battery charges to cope with unexpected faults
- Low dependency on the main grid based on the local-production-local-consumption policy

A battery management system (BMS) attached to each battery performs the power management of its neighborhood by manipulating the power flows from and into the battery. Each BMS communicates with its neighboring BMS’s through the communication links indicated by the blue dashed lines in Fig. 2. The purpose of this paper is to achieve the aforementioned objectives of the microgrid management by applying the SMPC method combined with the JIT-based PV power prediction to the BMS’s in a distributed manner.

As described in the previous section, we assume that the output of the i-th PV generator is expressed as

\[ S_i(t) = S_i^{\text{JIT}}(t) + \Delta S_i(t), \]

where \( S_i^{\text{JIT}} \) is the one-day prediction of \( S_i \) based on the JIT modeling technique, and \( \Delta S_i \) is the prediction error modeled by an AR model. In particular, \( \Delta S_i(t) \) is modeled by

\[ \Delta S_i(t) = (W_{\text{norm}} \cdot \text{PR} \cdot \alpha) \cdot \Delta y_i(t), \]
\[ \Delta y_i(t) = a_{i1} \Delta y_i(t-1) + a_{i2} \Delta y_i(t-2) + \cdots + a_{i\tau} \Delta y_i(t-\tau) + w_i(t), \]

where \( w_i \) is a zero mean Gaussian white noise process.

Hence, the modified PV power prediction is given by

\[ \hat{S}_i(t+k|t) = S_i^{\text{JIT}}(t+k|t) + \Delta \hat{S}_i(t+k|t), \]
\[ \Delta \hat{S}_i(t+k|t) = (W_{\text{norm}} \cdot \text{PR} \cdot \alpha) \cdot \Delta \hat{y}_i(t+k|t), \]
\[ \Delta \hat{y}_i(t+k|t) = a_{i1} \Delta \hat{y}_i(t+k-1|t) + a_{i2} \Delta \hat{y}_i(t+k-2|t) + \cdots + a_{i\tau} \Delta \hat{y}_i(t+k-\tau|t), \]
\[ \Delta \hat{y}(t-l|t) = y(t-l) - y^{\text{JIT}}(t-l), \quad (l = 1, 2, \ldots, \tau). \]

For simplicity, the demands \( D_i \) are assumed to be exactly known a priori to the BMS’s, while it is straightforward to extend the present method to the case where the prediction errors of the demands are present.

We denote the power flow from \( A \) to \( B \) by \( F_{AB} \). Especially, \( F_{iD_i} \) represents the flow from the main grid utility to the i-th demand. Also, let \( D_i \) and \( S_i \) be the index sets of the consumers (demands) and PV’s connected to the i-th battery, respectively. \( \mathcal{P}_i \) denotes the index set of the PV’s connected to the j-th demand \( D_j \).

For ease of notations, we will denote the k-step future value \( x(t+k) \) from the current time \( t \) by \( x[k] \), namely, \( x[k] := x(t+k) \). Moreover, We will abuse the notation to denote the sequence \( \{x[k]\}_{k=0}^{N} \) simply by \( x \).

3.2 Distributed SMPC

The BMS of the i-th battery determines its power flows \( F_{B_iD_j}, F_{S_iB_i} \) (\( j \in D_i, \ell \in S_i \)) in a receding horizon control fashion. Namely, at each time step, each BMS solves a certain finite-horizon optimal control problem, and apply the first value of the obtained optimal control sequence to the battery.

To be more specific, at time \( t \), the i-th BMS should find the optimal sequences of \( F_{B_iD_j}, F_{S_iB_i} \) (\( j \in D_i, \ell \in S_i \)) which minimize

\[ J_i := \frac{1}{2} \mathbb{E} \left\{ \sum_{k=0}^{N} P_{ik} (B_i[k+1] - B_i^{\text{max}})^2 + Q_{ik} F_{UD_i}[k]^2 \right\} \]

under the condition that the constraints (i)-(iv) below should be satisfied in a certain probabilistic sense, where \( N \) is the horizon length, and the positive numbers \( P_{ik} \) and \( Q_{ik} \) are the weights which represent the relative importance of the objectives.

(i) Battery capacity constraints:

\[ 0 \leq B_i[k+1] \leq B_i^{\text{max}}, \quad k = 0, \ldots, N, \]

(ii) Line capacity constraints:

\[ F_{B_iD_j}[k] \leq F_{B_iD_j} \quad \forall j \in D_i, \]
\[ F_{S_iB_i}[k] \leq F_{S_iB_i} \quad \forall \ell \in S_i, \quad k = 0, \ldots, N, \]

(iii) Battery charge dynamics:

\[ B_i[k+1] = B_i[k] - \sum_{j \in D_i} F_{B_iD_j}[k] + \sum_{\ell \in S_i} F_{S_iB_i}[k], \quad k = 0, \ldots, N, \]
\[ B_i[0] = B_i(t), \]
(iv) Supply-demand balancing:

\[ D_j[k] = F_{UD_j}[k] + F_{B, D_j}[k] + \sum_{m \in D_m} F_{B_m, D_j}[k] + \sum_{\ell, j \in D_{ij}} F_{S_{\ell}, D_j}[k] \quad \forall j \in D_1, \ k = 0, \ldots, N. \]

Note that the first term in \( J_i \) aims at the control objective of the battery charge reservations, and the second term aims at the local-production-local-consumption by reducing the supply from the main grid (utility).

For the constraints (i), \( B^\text{max}_i \) denotes the capacity of the \( i \)-th battery, and charge/discharge violating these constraints cannot happen. In the line capacity constraints (ii), \( E_{AB}^L \) and \( E_{AB}^U \) represent the lower and upper bounds on the power flow from \( A \) to \( B \). It may be noted that a negative \( E_{AB}^L \) allows a backward flow in the transmission line under consideration. The backward flow to the main grid utility means selling surplus electricity to it. As in the constraint (iii), the battery charge is dominated by the power exchange between the battery and the connected consumers (demands) and/or PV’s. A positive \( F_{B, D_j} \) implies discharging, and a positive \( F_{S_{\ell}, D_j} \) implies charging of the \( i \)-th battery. The constraint (iv) is the supply-demand balancing constraint for the \( j \)-th demand. Note that the constraint contains \( F_{S_{\ell}, D_j} \) which cannot be directly accessed by the \( i \)-th BMS. To obtain the predicted value of \( F_{S_{\ell}, D_j} \), the \( i \)-th BMS receives the prediction of \( F_{S_{\ell}, B_m} \), \( \ell \in S_m \) from the neighboring BMS’s. Then, \( F_{S_{\ell}, D_j}[k] \) can be expressed as

\[ F_{S_{\ell}, D_j}[k] = S_i[k] - \sum_{m \in S_m} F_{S_{\ell}, B_m}[k] \]

under the assumption that the predicted values of \( F_{S_{\ell}, B_m} \), \( m \in S_m \) received from the neighboring BMS’s are exact. For example, though \( F_{S_{\ell}, D_j} \) cannot be accessed by the BMS 1, it can compute \( F_{S_{\ell}, D_j} \) as \( F_{S_{\ell}, D_j} = S_1 - F_{S_{\ell}, B_2} \) by receiving the prediction of \( F_{S_{\ell}, B_2} \) from BMS 2.

As is mentioned above, the constraints (i)–(iv) must be satisfied in a probabilistic sense since the PV power generation \( S_i \) contains the random variable \( w_i := \{ w_i[0], \ldots, w_i[N] \} \). We thus introduce the chance constraint

\[ V(\{F_{B, D_j}\}_{j \in D_1}, \{F_{S_{\ell}, B_i}\}_{\ell \in S_i}) \geq 1 - \epsilon, \]

where

\[ V(\{F_{B, D_j}\}_{j \in D_1}, \{F_{S_{\ell}, B_i}\}_{\ell \in S_i}) := \text{Prob}\{w_i \in \mathbb{R}^{N+1} | (i)–(iv) \text{ are satisfied.}\}, \]

and \( \epsilon \) is a small positive constant given by the designer. Since it is difficult to directly treat the above chance constraint, we introduce the following deterministic optimization problem by taking \( n \) random samples of \( w_i \).

**Sampled Quadratic Programming** \( \text{SQP}_{i,n} \):

\[
\begin{align*}
\text{minimize} & \quad \{F_{B, D_j}\}_{j \in D_1}, \{F_{S_{\ell}, B_i}\}_{\ell \in S_i}, \\
\text{subject to} & \quad (i)–(iv) \text{ for } w_i = w_i^{(q)}, \ (q = 1, \ldots, n),
\end{align*}
\]

where \( w_i^{(q)}, \ (q = 1, \ldots, n) \) are the random samples of \( w_i \) according to its probabilistic distribution.

Notice that the objective function \( J_i \) is a quadratic function of \( \{F_{B, D_j}\}_{j \in D_1}, \{F_{S_{\ell}, B_i}\}_{\ell \in S_i} \), and the constraints are deterministic linear inequalities of these variables. Therefore, \( \text{SQP}_{i,n} \) is a deterministic quadratic programming problem which can be efficiently solved by an existing convex optimization algorithm.

According to Corollary 1 in Calafiore and Campi [10], the following proposition holds true for \( \text{SQP}_{i,n} \).

**Proposition 1** For given constants \( \epsilon, \delta \in (0, 1) \), take the number of samples so that

\[ n \geq d + 1 - \epsilon \delta - 1, \]

(16)

is satisfied, where \( d \) is the number of the decision variables, i.e. \( d = (N + 1)(|D_1| + |S_i|) \). Then, the optimal solution \( \{F_{B, D_j}\}_{j \in D_1}, \{F_{S_{\ell}, B_i}\}_{\ell \in S_i} \) of \( \text{SQP}_{i,n} \), if exists, satisfies the probabilistic inequality

\[
\text{Prob}\{V(\{F_{B, D_j}\}_{j \in D_1}, \{F_{S_{\ell}, B_i}\}_{\ell \in S_i}) \geq 1 - \epsilon \} \geq 1 - \delta.
\]

(17)

It is seen that the number of the constraints in \( \text{SQP}_{i,n} \) increases according to the number of the random samples. We suppress the increase of constraints by exploiting only the active constraints which correspond to either of \( \Delta S^\text{min}_i[k] = \min \{\Delta S_i[0], \Delta S_i[1], \cdots \Delta S_i[N]\} \) or \( \Delta S^\text{max}_i[k] = \max \{\Delta S_i[0], \Delta S_i[1], \cdots \Delta S_i[N]\} \).

### 4 Simulation

#### 4.1 Simulation setting

We perform a numerical simulation for the microgrid model depicted in Fig. 2. The simulation model is constructed with reference to the small scale microgrid model in the reference [11].

The computer setup and parameter setting for the simulation are summarized in Tables 2 and 3. In particular, the true PV power generation in this simulation is calculated from the real solar irradiance data described in Table 2 by using the formula (11). Moreover, we employ the time-varying weights \( P_{ik}, Q_{ik} \) (\( i = 1, 2, 3 \)) as shown in Table 3 according to the priorities of the control objectives. Namely, the weights \( Q_{ik} \) are relatively large until 9:00 to emphasize the local production local consumption policy, while they are small after 9:00 in order to reserve sufficient energy in the batteries.
Table 2: Simulation Setting

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Database</strong></td>
<td>Jun. 1, 2011 to Dec. 31, 2015 (5 years)</td>
</tr>
<tr>
<td><strong>Input Data</strong></td>
<td>Aug. 14, 2016 (a sunny day)</td>
</tr>
<tr>
<td><strong>Area</strong></td>
<td>Osaka, Japan (lat. 35°40.9’N, long. 125°31.1’E)</td>
</tr>
<tr>
<td><strong>K-NN</strong></td>
<td>$K = 20$</td>
</tr>
<tr>
<td><strong>Software</strong></td>
<td>MATLAB/Simulink R2016b</td>
</tr>
<tr>
<td><strong>PC</strong></td>
<td>OS: Windows10 64-bit CPU: Intel® Core <a href="mailto:i7-5820@3.30GHz">i7-5820@3.30GHz</a> RAM: 32.00GB</td>
</tr>
</tbody>
</table>

Table 3: Simulation Parameters

<table>
<thead>
<tr>
<th>$\tau/K_{AR}$</th>
<th>$3\text{steps}/10\text{Points}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizon Length</td>
<td>$N = 5\text{ steps}$</td>
</tr>
<tr>
<td>Sampling Period</td>
<td>0.5[h]</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>1.3</td>
</tr>
<tr>
<td>$W_{\text{min}}$</td>
<td>5[kWh]</td>
</tr>
<tr>
<td>PR</td>
<td>0.80(=80%)</td>
</tr>
<tr>
<td>Maximum Demand</td>
<td>7.5 [kWh]</td>
</tr>
<tr>
<td>$B(0)/B_{\text{max}}$</td>
<td>14 / 20 [kWh]</td>
</tr>
<tr>
<td>$(\delta, \epsilon, n)$</td>
<td>(0.15, 0.15, 600)</td>
</tr>
<tr>
<td>$w_i$</td>
<td>$N(0, 0.001)$</td>
</tr>
<tr>
<td>$(P_i, Q_i)$ [before 9:00]</td>
<td>(1, 60), (1, 80), (1, 30)</td>
</tr>
<tr>
<td>$(P_i, Q_i)$ [after 21:00]</td>
<td>(1, 10), (1, 20), (1, 10)</td>
</tr>
<tr>
<td>$(P_i, Q_i)$ [otherwise]</td>
<td>(1, 10), (1, 20), (1, 10)</td>
</tr>
</tbody>
</table>

The weights $w_k, k = 1, \ldots, 11$ in the similarity calculation formula (2) for the JIT modeling are obtained by the multiple regression analysis, and shown in Table 5.

4.2 Simulation result

![Fig. 3: PV Power Prediction](image)

Fig. 3 shows the results of PV power prediction. It is seen that the prediction by the combination of the JIT modeling and the AR model (solid curve) is closer to the true value (dashed) than the prediction by the JIT modeling alone (dotted). The RMS values of the prediction errors are 0.2764 and 0.3679 for the combined prediction method and the JIT modeling alone, respectively.

Table 4: Line Capacity Constraints

<table>
<thead>
<tr>
<th>Component</th>
<th>$F_{UD_1,2,3}$ (max/min)</th>
<th>$8/-6$ [kWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{B_1,D_1}$ (max/min)</td>
<td>$8/0$ [kWh]</td>
<td></td>
</tr>
<tr>
<td>$F_{S_1,D_1}$ (max/min)</td>
<td>$10/0$ [kWh]</td>
<td></td>
</tr>
<tr>
<td>$F_{S_2,D_1}$ (max/min)</td>
<td>$8/0$ [kWh]</td>
<td></td>
</tr>
<tr>
<td>$F_{B_1,D_2}$ (max/min)</td>
<td>$10/0$ [kWh]</td>
<td></td>
</tr>
<tr>
<td>$F_{S_1,D_2}$ (max/min)</td>
<td>$8/0$ [kWh]</td>
<td></td>
</tr>
<tr>
<td>$F_{S_2,D_2}$ (max/min)</td>
<td>$10/-6$ [kWh]</td>
<td></td>
</tr>
<tr>
<td>$F_{S_1,D_3}$ (max/min)</td>
<td>$8/0$ [kWh]</td>
<td></td>
</tr>
<tr>
<td>$F_{B_3,D_3}$ (max/min)</td>
<td>$10/0$ [kWh]</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Weighting Factors for the JIT Modeling

<table>
<thead>
<tr>
<th>Component</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day Length</td>
<td>0.54</td>
</tr>
<tr>
<td>Sun Altitude</td>
<td>0.86</td>
</tr>
<tr>
<td>Atmospheric Pressure</td>
<td>0.26</td>
</tr>
<tr>
<td>Temperature</td>
<td>0.68</td>
</tr>
<tr>
<td>Wind (East- West)</td>
<td>0.05</td>
</tr>
<tr>
<td>Wind (South- North)</td>
<td>0.006</td>
</tr>
<tr>
<td>Humidity</td>
<td>0.24</td>
</tr>
<tr>
<td>Lower Cloudiness</td>
<td>0.07</td>
</tr>
<tr>
<td>Middle Cloudiness</td>
<td>0.04</td>
</tr>
<tr>
<td>Upper Cloudiness</td>
<td>0.03</td>
</tr>
<tr>
<td>Rain Fall</td>
<td>0.01</td>
</tr>
</tbody>
</table>

It is seen from Fig. 4 that each BMS supplies sufficient power to the consumers (demands), while there are some imbalances between the demands and the supplies from the PV’s and batteries due to the prediction errors of the PV power supplies.

As is seen from Fig. 5, each battery delivers electric power in the morning and charges power in the daytime. This implies that the resulting battery behaviors exhibit an effect similar to peak shifting.

Figs. 6–8 show the power flows of the BMS 1, 2 and 3. For “JIT” (Figs. 6(a)–8(a)), the simulation is carried out under the assumption that the PV power predictions are exact, namely, $S_i(t) = \hat{S}_i$ at any time $t$. On the other hand, “Real” in Figs. 6(a)–8(b) means that the simulation is carried out in the presence of the PV prediction errors. It is seen from the results in the “JIT” case that, with highly accurate PV power predictions, it is possible to manage the power flows without violating the constraints, while the errors of the PV power predictions greatly influence the control performance. The results in the “Real” case show that the proposed method performs well without violating the constraints even in the presence of prediction errors.
5 Conclusion

We have proposed an distributed SMPC method for the microgrid power management using on the PV power predictions. Although each BMS is pursuing only its local benefit in a distributed manner, it is verified from the simulation results that the global objectives for the microgrid management are achieved without violating the capacity constraints because of the information exchange among the neighboring BMS's.

To guarantee the global benefit of the overall microgrid, the role of a coordinator, or a supervisor, aggregating information from all the BMS's will be crucial. As a future work, it remains to develop a control method for distributed stochastic microgrid management including such a coordinator.

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References


Fig. 8: Power Flows (BMS 3)


