Distributed cooperative control strategy for islanded microgrids

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Abstract. In this paper, a distributed cooperative control strategy for islanded microgrids (MGs) is proposed, to minimize the total generation cost of distributed generators (DGs), and maintain the state of charge (SoC) balancing of battery energy storage systems (BESSs). First, a consensus-based economic dispatch (ED) strategy is proposed, to achieve the minimum total generation cost of DGs, while the aggregated power output of DGs meets the power dispatch command from the supervisory control system. Further, an SoC-based droop control strategy is developed for BESSs, to maintain the SoC balancing and power balance in the islanded MG simultaneously. Compared with the centralized control schemes, the proposed cooperative control strategy is fully distributed such that it simply requires local information exchange without the necessity of a central controller. More importantly, the proposed cooperative control strategy is able to achieve multiple control objectives in a unified framework. Finally, the simulation results in an islanded MG with renewable energy and time-varying load demands are presented, to demonstrate the effectiveness of the proposed distributed cooperative control strategy.

1. Introduction

The islanded microgrid (MG) is considered as a small scale smart grid that facilitates the flexible integration of renewable energy such as wind and solar generation by means of distributed generators (DGs) [1]. Note that, the intermittency of renewable energy and low-inertia nature of the power electronic converters result in the demand-supply mismatch in the islanded MG. Therefore, the battery energy storage systems (BESSs) are integrated into the islanded MG, to enhance its flexibility and stability in terms of smoothing the variations of renewable energy and load demands [2].

For an islanded MG consisting of DGs and BESSs, the flexible control methods are prerequisites for its stable and economic operation. The centralized paradigm is extensively applied for the MG control while centralized control has some limitations. On the contrary, the distributed control is simply based on local information and cooperation, which effectively overcomes the limitations of centralized control [3-5]. Therefore, it is desirable to develop distributed control methods for the MG, to enable the peer-to-peer communication among DGs without the necessity of a central controller and a comprehensive communication network. In such a context, the control method of the islanded MG is now evolving toward the distributed and decentralized control with the increasing number of heterogeneous and geographically dispersed DGs.
The economic dispatch (ED) is an essential problem in islanded MG. To minimize the cost of generation, we can choose the incremental cost of DG as the consensus variable, and then the consensus of the incremental cost can be ensured by update rules of the consensus algorithm, to satisfy the equal incremental cost criterion, i.e., the total generation cost of the MG is minimized. Following this idea, the incremental cost consensus algorithms were proposed to solve the ED problem in a distributed manner [6-8]. Note that DGs and the price-responsive demands can adjust their generation and consumption levels simultaneously in response to variations in the MG. Therefore, considering the pricing signal, the ED and demand response problems were solved in an integrated manner, to minimize the total generation cost of DGs while maximizing the social welfare of the demand side simultaneously [9-10].

On the other hand, the BESSs play an increasingly important role in the MG. Note that the unbalanced state of charge (SoC) of BESSs may possibly result in unintentional outages of BESSs and deterioration of system performance, while the power capacity of all BESSs and the capability of stabilizing the MG remain the maximum, when SoCs of all BESSs are balanced. Therefore, the BESSs in the MG should be charged or discharged in a balanced manner all the time to fully utilize of battery capacities and avoid overcharging or over-discharging [11-13]. In recent years, several studies have been conducted for SoC balancing in the AC MGs. For instance, the SoC balancing strategies incorporating the distributed secondary frequency control were investigated [14-16]. Later, the communication delays were explicitly considered in the SoC balancing [17]. By choosing the SoC or virtual impedance of the BESS as the consensus variable, the SoC balancing of BESSs was ensured by iterative update rules of the consensus algorithm [18-20].

Note that all of the aforementioned studies simply focused on the ED of DGs or SoC balancing of BESSs, and did not consider the cooperation among DGs and BESSs. Therefore, this paper proposes a distributed cooperative control strategy for ED of DGs and SoC balancing of BESSs in the islanded MG, which is rarely investigated in the existing literatures. First, a leader DG calculates the optimal incremental cost in terms of the power dispatch command from the supervisory control system, which is simply available to the leader DG and determines the aggregated power output of DGs. Next, the consensus-based ED strategy drives the incremental costs of DGs to the optimal value, satisfying the equal incremental cost criterion. Further, an SoC-based droop control strategy is developed for BESSs, to maintain the power balance in the islanded MG, and adjust the power outputs of BESSs in terms of the average SoC of all BESSs, to achieve the SoC balancing of BESSs. Finally, simulation results in an islanded MG with renewable energy and time-varying load demands are presented, to demonstrate the effectiveness of the proposed distributed cooperative control strategy.

Compared to the existing approaches, the salient features of the proposed cooperative control strategy are summarized as follows. Firstly, it is fully distributed such that it simply requires sparse communication links and necessary information exchange among neighboring DGs and BESSs. Secondly, it can realize multiple control objectives in a unified framework, i.e., the minimum total generation cost of DGs, the aggregated power output of DGs meets the power dispatch command and SoC balancing of BESSs.

The rest of the paper is organized as follows. The structure and parameters of the islanded MG are introduced in Section 2. In addition, the problems about ED and SoC balancing are formulated in Section 3. In Section 4, the distributed cooperative control strategy for DGs and BESSs is presented. Later, in Section 5, three simulation cases are carried out to evaluate the performances of the proposed cooperative control strategy, and the simulation results are analyzed and discussed. Finally, Section 6 concludes the paper.

2. The structure and parameters of the islanded MG
In this paper, an example islanded MG shown in Figure 1 is considered, which consists of a photovoltaic (PV) generation system, a wind generation system, DGs and BESSs. The specifications of generation units are listed in Figure 1, and the line impedance is set at 0.099 + j0.093 Ω/km [21]. Here, both PV and wind generation systems operate in maximum power point tracking (MPPT)
control mode. Additionally, DG1, DG2, DG3 and DG4 are ideal dc voltage sources $V_d$ that can be regarded as dc-links of dispatchable DGs, e.g., fuel cells and micro gas turbines [22], and they are connected to the MG through the converters working in active and reactive power (PQ) control mode. Moreover, all BESSs operate in terms of the proposed SoC-based droop control strategy, which will be elaborated in Section 4.

![Dispatchable Distributed Generators (PQ Control)](image)

**Figure 1.** Schematic diagram of an islanded MG.

### 3. Problem formulation

#### 3.1. Economic dispatch of DGs

In this paper, it is assumed that the PV and wind generations are free. However, the $i$-th dispatchable DG has a quadratic generation cost function, which takes the following forms

$$C_i(P_i) = a_i \cdot P_{G,i}^2 + b_i \cdot P_{G,i} + c_i$$

where $P_{G,i}$ is the power output of $i$-th dispatchable DG, and $a_i$, $b_i$ and $c_i$ are cost coefficients. The cost coefficients and power limits of DGs are listed in Table 1 [23], where $P_{G,i}^{\text{min}}$ and $P_{G,i}^{\text{max}}$ are lower and upper limits of active power output of $i$-th dispatchable DG, respectively.

| DG   | a   | b   | $P_{G,i}^{\text{min}}$ | $P_{G,i}^{\text{max}}$ |
|------|-----|-----|------------------------|------------------------|
| DG1  | 0.094 | 1.22 | 0                      | 80kW                   |
| DG2  | 0.078 | 3.41 | 0                      | 60kW                   |
| DG3  | 0.105 | 2.53 | 0                      | 40kW                   |
| DG4  | 0.082 | 4.02 | 0                      | 45kW                   |

First, the power outputs of dispatchable DGs are regulated in such a way that the aggregated power output meets the power dispatch command, that is,
where \( n \) is the number of dispatchable DGs, \( P_d \) is the power dispatch command.

Further, we minimize the total generation cost of dispatchable DGs, which is an ED problem and can be formulated as follows

\[
\min \sum_{i=1}^{n} C_i(P_{G,i}) = \min \sum_{i=1}^{n} (a_i \cdot P_{G,i}^3 + b_i \cdot P_{G,i} + c_i)
\]

(3)

\[
\sum_{i=1}^{n} P_{G,i} = P_d
\]

(4)

\[
P_{G,i}^{\min} \leq P_{G,i} \leq P_{G,i}^{\max}
\]

(5)

The ED problem can be solved by the Lagrangian method, and the corresponding Lagrangian function takes the following forms [9, 24],

\[
L(P_{G,1}, P_{G,2}, \ldots, P_{G,n}) = \sum_{i=1}^{n} C_i(P_{G,i}) + \lambda \cdot (P_d - \sum_{i=1}^{n} P_{G,i}) + \sum_{i=1}^{n} u_i (P_{G,i} - P_{G,i}^{\max}) + \sum_{i=1}^{n} u_i (P_{G,i} - P_{G,i}^{\min})
\]

(6)

where \( \lambda \), \( u_i \) and \( \bar{u}_i \) are Lagrange multipliers.

Finally, the solution to the ED problem can be obtained, which is the equal incremental cost criterion, and it takes the following forms

\[
\begin{align*}
\lambda_i &= \frac{\partial C_i(P_{G,i})}{\partial P_{G,i}} = \lambda_i^* & P_{G,i}^{\min} < P_{G,i} < P_{G,i}^{\max} \\
\lambda_i &= \frac{\partial C_i(P_{G,i})}{\partial P_{G,i}} \leq \lambda_i^* & P_{G,i} = P_{G,i}^{\max} \\
\lambda_i &= \frac{\partial C_i(P_{G,i})}{\partial P_{G,i}} \geq \lambda_i^* & P_{G,i} = P_{G,i}^{\min} \\
\frac{\partial C_i(P_{G,i})}{\partial P_{G,i}} &= 2a_i \cdot P_{G,i} + b_i
\end{align*}
\]

(7)

where \( \lambda_i \) and \( \lambda_i^* \) are incremental cost and optimal incremental cost of \( i \)-th DG, respectively.

The equal incremental cost criterion denotes that the total active power generation cost of DGs is minimized, when the equal incremental cost criterion is satisfied.

3.2. SoC balancing of BESSs

In the islanded MG, due to the uncertainty of PV and wind power generations and time-varying load demands, the MG experiences the supply-demand mismatch. Therefore, the power required from BESSs for power balance is calculated as follows

\[
\sum_{i=1}^{n} P_{B,i} = P_{\text{load}} + P_{\text{loss}} - \sum_{i=1}^{n} P_{G,i} - P_{\text{RG}}
\]

(8)

\[
P_{\text{loss}} = 5\%P_{\text{load}}
\]

(9)

\[
P_{B,i}^{\min} \leq P_{B,i} \leq P_{B,i}^{\max}
\]

(10)
where \( m \) is the number of BESSs, \( P_{B_i} \) is the output power of \( i \)-th BESS, \( P_{load} \) is the total load demand in the MG, \( P_{loss} \) is the transmission loss and it is about 5% of the total load demand [10, 25, 26], \( P_{RG} \) is the total active power output of PV and wind generation systems, \( P_{min}^{B_i} \) and \( P_{max}^{B_i} \) are lower and upper limits of active power output of \( i \)-th BESS, respectively.

Based on the power balance, the power outputs of BESSs are regulated in such a way that the SoCs of BESSs converge to a consensus, i.e., SoC balancing. First, the SoC of BESS is estimated in terms of the coulomb counting method, which is expressed as follows

\[
\text{SoC}_i = \text{SoC}_0 - \frac{1}{C_{e,i}} \int_i b_i dt
\]

where \( \text{SoC}_0 \), \( C_{e,i} \) and \( i b_i \) are initial SoC, capacity and output current of \( i \)-th BESS, respectively.

Further, we assume that the output voltages of BESSs are the same and converter loss can be omitted, and there exists the following approximations for BESSs

\[
V_{b_i} = \ldots = V_{b_j} = \ldots = V_{b_m}
\]

\[
P_{B_i} = V_{b_i} \cdot i_{b_i}
\]

where \( m \) is the number of BESSs, \( V_{b_i} \) and \( P_{B_i} \) are output voltage and power of \( i \)-th BESS, respectively.

Consequently, combining (11), (12) and (13), the SoC estimation can be rewritten as follows

\[
\text{SoC}_i = \text{SoC}_0 - \mu \int P_{b_i} dt
\]

Where \( \mu = \frac{1}{(C_{e,i} V_{b_i})} \).

It can be seen from (14) that the SoC of BESS is determined by initial SoC and output power. Therefore, the SoC balancing of BESSs can be achieved by regulating the active power outputs of BESSs.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Figure2.png}
\caption{Communication network for DGs and BESSs.}
\end{figure}

4. Distributed cooperative control strategy

4.1. Distributed economic dispatch strategy for DGs

In this paper, a spare communication network is designed for DGs and BESSs, as shown in Figure 2, and DG1 and BESS1 are randomly selected as leader DG and BESS, respectively. As we can see in the Figure 2, it is a distributed communication network, which doesn’t need a central controller. In addition, limited information is transmitted among the agents. Receiving the power dispatch command \( P_{p} \) from the supervisory control system, the optimal incremental cost \( \lambda \) is calculated in terms of (15) and (16), provided that the cost coefficients of DGs are available to DG1 and the SoC of BESS\(_i\) is within the allowable limits,
\[ P_{G,i} = \frac{\lambda^* - b_i}{2a_i} \]  
\[ P_{G,1} + P_{G,2} + P_{G,3} + P_{G,4} = P_D \]  

Later, the optimal incremental cost \( \lambda^* \) is transmitted to the neighboring DGs through the communication network shown in Figure 2. Finally, in order to drive the incremental costs of DGs to the optimal value, a theorem is proved for deriving the control laws from a given communication network. In this paper, the control law is based on the distributed communication network shown in Figure 2, i.e., matrix \( A \) and \( M \) depends on the structure of the network. In terms of the control laws, agents regulate the active power outputs of dispatchable DGs to which they connect, to achieve the minimum total generation cost of DGs.

**Theorem:** If agents calculate the reference incremental costs at the next control step in terms of (17) and (18), and apply the results to regulate power outputs of dispatchable DGs to which they connect, then the equal incremental cost criterion is satisfied, namely, \( \lambda_1 = \ldots = \lambda_i = \ldots = \lambda_n \)

\[ \lambda_{[t+1]} = M\lambda_{[t]} \]  
\[ M = \frac{1}{k+1} (A - D) + I \]  

where \( \lambda_{[t+1]} = [\lambda_1[t+1], \ldots, \lambda_i[t+1], \ldots, \lambda_n[t+1]]^T \); \( \lambda_{[t]} = [\lambda_1[t], \ldots, \lambda_i[t], \ldots, \lambda_n[t]]^T \); \( D \) is an \( n \times n \) and diagonal outdegree matrix, whose elements \( d_i \) is the number of outgoing communication links of agent; \( k \) is the maximum outdegree of all agents; \( I \) is an identity matrix.

**Proof:** First, \( A - D \) and \( M \) are obtained as follows

\[ A - D = \begin{bmatrix} a_{i1} - d_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{nj} & \cdots & a_{nj} - d_{nj} & \cdots & a_{nn} \end{bmatrix} \]  
\[ M = \begin{bmatrix} a_{i1} & \cdots & a_{i1} & \cdots & a_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{nj} & \cdots & a_{nj} - d_{nj} & \cdots & a_{nn} \\ k + 1 & \cdots & k + 1 & \cdots & 1 \\ k + 1 & \cdots & k + 1 & \cdots & 1 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ k + 1 & \cdots & k + 1 & \cdots & 1 \\ a_{nj} & \cdots & a_{nj} - d_{nj} & \cdots & a_{nn} \end{bmatrix} \]  

For a strongly connected graph, the sum of all elements in \( i \)-th row and \( i \)-th column equal \( d_i \) are equal. Namely, the following equations are satisfied

\[ \sum_{j=1}^{n} a_{ij} = \sum_{j=1}^{n} a_{ji} = d_i \]  

Consequently, the sum of \( i \)-th row of \( M \) can be calculated

\[ \sum_{j=1}^{n} m_{ij} = \frac{1}{k+1} (a_{i1} + \cdots + a_{ni} - d_i + k+1) \]  
\[ = \frac{1}{k+1} (\sum_{j=1}^{n} a_{ij} - d_i + k+1) = 1 \]
Applying condition (21) to (22), we obtain the final result as follows

\[ \sum_{j=1}^{n} m_{ij} = 1 \]  

(23)

Similarly, the sum of \(i\)-th column of \(M\) can be calculated

\[ \sum_{j=1}^{n} m_{ji} = 1 \]  

(24)

In other words, the sums of elements in each row and column are all ones, i.e., \(M \cdot e = e\) and \(M^T \cdot e = e\), with \(e = [1, 1, \ldots, 1]^T\). Moreover, all elements of \(M\) are greater or equal to zero, i.e., \(m_{ij} \geq 0\). Therefore, it can be concluded that \(M\) is a doubly stochastic matrix.

According to the Gerschgorin’s Disk Theorem and Perron Frobenius Lemma, it yields the following equation

\[ \lim_{t \to \infty} M^t = \frac{ee^T}{n} \]  

(25)

In terms of (25), the system will reach consensus as \(t\) approaches infinity as represented

\[ \lim_{t \to \infty} \lambda(t + 1) = \lim_{t \to \infty} M^t \lambda(0) = \frac{ee^T}{n} \lambda(0) \]  

(26)

which indicates that the incremental costs of DGs will converge to a consensus, i.e., \(\lambda_i = \cdots = \lambda_i = \cdots = \lambda_i\).

That is, the theorem is proved.

4.2. Distributed SoC-based droop control strategy for BESSs

The droop control is one of the most popular methods for active power sharing. In this section, an SoC-based droop control strategy is developed, which adds an item with respect to the SoC of BESS to the traditional \(P-f\) droop control and can be expressed as follows

\[ f_i = f_{\text{max}} - m_i \cdot P_{Bi} + K_p (\text{SoC}_{i} - \text{SoC}_{\text{avg}}) \]  

\[ m_i = \frac{f_{\text{max}} - f_{\text{min}}}{P_{\text{max},Bi}} \]  

(27)

(28)

where \(f_i\) is the frequency of BESS\(_i\), and \(f_{\text{max}} = 51\) Hz and \(f_{\text{min}} = 49\) Hz are maximum and minimum frequencies allowed by the MG [27], respectively. The parameter \(m_i\) is the \(P-f\) droop coefficient, and \(K_p\) is the proportional coefficient which is taken as 30 in this paper. In addition, the parameters \(\text{SoC}_{i}\), \(\text{SoC}^{\text{avg}}_{\text{avg}}\) and \(P_{\text{max},Bi}\) are the SoC of BESS\(_i\), the average SoC of all BESSs and the maximum power of BESS\(_i\).

In order to obtain the average SoC of all BESSs, the SoCs of BESSs are considered as the state values of agents, and the average SoC of all BESSs is obtained by iterative update rules formulated in (17) and (18). Namely, the communication network shown in Figure 2 is utilized, where the agents of BESSs can exchange information with the connected agents. From the (17) and (18), it can be seen that the agents will keep updating their state values according to their own values and the neighboring values until the state values converge to consensus, i.e., the average SoC is obtained.

Furthermore, the Equation (27) can be rewritten as

\[ P_{Bi} = \frac{f_{\text{max}} - f_i + K_p (\text{SoC}_{i} - \text{SoC}_{\text{avg}})}{m_i} \]  

(29)
where the $m_1 = m_2 = \ldots = m_l$ for BESSs.

Consequently, it is concluded from (29) that in the discharging operation mode, if $\text{SoC}_i > \text{SoC}_{\text{avg}}$, then the discharging power of BESS$_i$ is larger than those of other BESSs. As a result, the decreasing speed of SoC$_i$ is higher than those of other BESSs and the SoCs are gradually balanced. Meanwhile, the power outputs of BESSs are equalized. Similarly, in the charging mode, if $\text{SoC}_i > \text{SoC}_{\text{avg}}$, then the charging power of BESS$_i$ is less than those of other BESSs. As a result, the increasing speed of SoC$_i$ is lower than those of other BESSs and the SoCs are gradually balanced. Meanwhile, the power outputs of BESSs are equalized.

The schematic diagram of SoC balancing for BESSs is illustrated in Figure 3. Firstly, BESSs exchange the information of SoC with their neighbors on the distributed communication network shown in Figure 2. Later, the average SoC is obtained in terms of the consensus algorithm as shown in Figure 3. Further, the proposed SoC-based droop control strategy adjusts the power outputs of BESSs in terms of the average SoC, to achieve the SoC balancing of BESSs.

5. Results

In order to evaluate the performance of our strategy, three simulation cases are carried out on an islanded MG shown in Figure 1, which is established in MATLAB/Simulink.

5.1. Case 1: power dispatch command tracking performance

In this case, the active power outputs of PV and wind generation systems and load demand remain constant. The initial SoCs of BESS1, BESS2, BESS3 and BESS4 are 1, 0.96, 0.92 and 0.88, respectively. Later, at $t = 200$ s, the power dispatch command $P_D$ for DGs changes from 60 kW to 80 kW. Under this situation, the responses of DGs to the change of $P_D$ are depicted in Figure 4. Figure 4(a) indicates that the active power outputs of DGs increase, and the aggregated power output of DGs converges to 80 kW. Figure 4(b) shows that the supply-demand mismatch is compensated by BESSs, to maintain the power balance in the islanded MG, and the power outputs of BESSs are equalized. Further, as shown in Figure 4(c), the proposed cooperative control strategy achieves the consensus of
incremental costs of DGs, i.e., the total generation cost of DGs is minimized. Moreover, it can be seen from Figure 4(c) that the SoC balancing of BESS is achieved.

**Figure 4.** Case 1: simulation results when the power dispatch command changes: (a) the active power outputs and aggregated power output of DGs; (b) the active power outputs of BESSs; (c) the incremental costs of DGs and SoCs of BESSs.

5.2. Case 2: responses to time-varying load demands and power outputs of intermittent DGs

In this case, the active power outputs of DGs are kept constant, i.e., the power dispatch command for DGs remains at 80 kW, as shown in Figure 5(a). On the other hand, the active power outputs of intermittent DGs change over time, and the total load demand decreases dramatically at \( t = 180 \) s. As a result, the active power outputs of all BESSs change simultaneously, fulfilling the generation-demand equality constraint in the MG, as shown in Figure 5(b). Furthermore, it can be seen from Figure 5(c) that the incremental costs of DGs and SoCs of BESSs converge to consensuses, respectively. The simulation results demonstrate that the proposed cooperative control strategy ensures the minimum generation cost of DGs and SoC balancing of BESSs simultaneously, even under the time-varying supply-demand imbalance condition.

**Figure 5.** Case 2: simulation results when the active power outputs of intermittent DGs and load demands change simultaneously: (a) the active power outputs and aggregated power output of DGs; (b) the active power outputs of BESSs; (c) the incremental costs of DGs and SoCs of BESSs.

5.3. Case 3: transferring between charging and discharging operation modes

In this case, the active power outputs of PV and wind generation systems and load demands remain constant. On the other hand, the power dispatch command for DGs changes, and the power outputs and aggregated power output of DGs follow the power dispatch command, as shown in Figure 6(a). On the other hand, in order to maintain the power balance in the islanded MG, the BESSs absorb and inject the power from or to the MG, so the transferring between charging and discharging modes is tested.

As shown in Figure 6(a), the BESSs first operate in discharging mode, and then change to charging mode. During the discharging process, SoCs are gradually balanced and the power outputs are equalized with the proposed cooperative control strategy. At \( t = 200 \) s, the power dispatch command for DGs is increased from 60 kW to 120 kW, resulting in the surplus power in the islanded MG.
Therefore, the BESSs absorb the surplus power in the islanded MG to maintain the power balance, as shown in Figure 6(b). The incremental costs of DGs and SoCs of BESSs are shown in Figure 6(c), where the proposed cooperative control strategy always maintains the consensus of incremental costs of DGs, as well as the SoC balancing of BESSs.

Figure 6. Case 3: simulation results when BESSs transfer between the discharging and charging modes: (a) the active power outputs and aggregated power output of DGs; (b) the active power outputs of BESSs; (c) the incremental costs of DGs and SoCs of BESSs.

6. Conclusion
In order to minimize the total generation cost of DGs and maintain the SoC balancing of BESSs, a distributed cooperative control strategy is proposed. Specifically, a consensus-based ED strategy is proposed, to minimize the total generation cost of DGs, and the aggregated power outputs of DGs meet the power dispatch command from supervisory control system. In addition, an SoC-based droop control strategy for BESS is developed, which adjusts the power outputs of BESSs in terms of the average SoC, to achieve the SoC balancing of BESSs and maintain the power balance in the islanded MG. Finally, the simulation results show that with the proposed cooperative control strategy, the SoC balancing of BESSs and the total power generation cost minimization of DGs can be achieved even if the power dispatch command and power demand change over the time. That is, the feasibility and effectiveness of the proposed cooperative control strategy are verified. In the future, the physical verification platform will be established, so as to conduct the experimental demonstration, and how to obtain the power dispatch command in a distributed manner is also one of our future works.

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