Prespecified-Time Observer-Based Distributed Control of Battery Energy Storage Systems

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Abstract—The distributed control of battery energy storage systems (BESSs) plays an important role in the practical operation of microgrid. This brief studies the state-of-charge (SoC) balancing and the total charging/discharging power tracking issues for BESSs with multiple distributed heterogeneous battery units under the premise that only partial battery units can access the desired power. First, two distributed prespecified-time observers are proposed to estimate average battery units state and average desired power respectively. Second, a novel distributed BESSs control strategy based on prespecified-time observers is proposed, which realizes SoC balancing and power tracking of BESSs assuming only partial battery units can access the desired power. Two distinctive advantages of this brief are (i) both the average desired power and the average battery state can be accurately estimated within the prespecified time, which can be determined in advance and independent of initial states or control parameters, and (ii) the communication costs are reduced effectively and single-point failures can be avoided. Finally, two simulation examples are given to verify the effectiveness and superiority of the proposed control strategy.

Index Terms—Battery energy storage system, State-of-charge, Power tracking, Distributed control, Prespecified-time observer.

I. INTRODUCTION

ENERGY storage system is an indispensable part of microgrid, which can reduce energy loss while ensuring power quality and reliability [1]. Among all kinds of energy storage technologies such as supercapacitor, superconducting magnetic, etc., BESS has an irreplaceable position in microgrid because of its advantages of fast response speed, high energy density, high efficiency and flexible configuration [2], [3]. During past decades, various types of BESSs are rapidly integrated into microgrid [4]. Despite their continuous advances in electrochemical technology, the control of BESSs remains a very challenging problem [5].

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and certain parameters of BESSs, which restricts its applications. Within the framework of finite-time stability, [14] studies the distributed secondary frequency and voltage control of isolated island microgrid. Although the fixed-time observer is proposed in [15], the setting time related to the parameter of the proposed control strategy. Note that in the framework of prespecified-time stability, the settling time can be preset according to the task requirements, independent of the initial conditions and other parameters of the underlying systems, which makes it more desirable. To the best of our knowledge, the SoC balancing and the total charging/discharging power tracking issues for heterogeneous BESSs has not been fully investigated, which greatly motivates the present study, the substantial challenges lie in the following aspects:

1) To improve the control rate and accuracy, how to design prespecified-time observers to ensure that the accurate estimation of the average desired power and the average battery unit state is completed within the prespecified time is a problem to be solved.

2) To reduce communication costs and avoid single-point failure, how to cooperative control BESSs on the premise that only partial battery units can access the desired power is a problem to be solved.

Inspired by the above observations, this brief addresses the problem of the SoC balancing and the total charging/discharging power tracking for heterogeneous BESSs. The main contributions and novelties of the present work are as follows:

1) Different from the asymptotic observers/fixed-time observers [10] and the fixed-time observers [15], two new prespecified-time observers are proposed by introducing piecewise time function. It is shown that both the average desired power and the average battery state can be accurately estimated within the prespecified time.

2) A novel distributed BESSs control strategy based on prespecified-time observers is proposed, which realizes SoC balancing and power tracking of BESSs assuming only partial battery units can access the desired power.

II. PRELIMINARIES AND SYSTEM DESCRIPTION

A. Preliminaries

In this section, graph theory is employed to describe the communication of BESSs, in which vertex \( i \in \mathcal{V} \) refers to battery unit \( i \) and edge \((i, j) \in \mathcal{E}\) refers to the interconnection between the battery units \( i \) and \( j \), where \( \mathcal{V} \) and \( \mathcal{E} \) denote the vertex set and edge set, respectively. The adjacency matrix \( A = [a_{ij}] \) associated with graph \( G \) is defined as \( a_{ij} = a_{ji} = 0 \) if there is no communication link between unit \( i \) and unit \( j \), otherwise \( a_{ij} = a_{ji} = 1 \). The neighboring set of agent \( i \) is represented by \( \mathcal{N}_i = \{ j \in \mathcal{V} : (i, j) \in \mathcal{E} \} \). The Laplacian matrix of graph \( G \) is defined as \( L = [l_{ij}] \), where \( l_{ij} = -a_{ij} \) if \( i \neq j \) and \( l_{ii} = \sum_{k=1,k \neq i}^{N} a_{ik} \). Obviously, the Laplacian \( L \) is symmetric with eigenvalues \( 0 = \lambda_1(L) < \lambda_2(L) \leq \lambda_3 \leq \cdots \leq \lambda_N(L) \). A graph is connected if there exists a path between any two distinct nodes.

B. System Description

Consider a class of heterogeneous BESSs with \( N \) battery units, described as follows based on the Coulomb counting method,

\[
\begin{align*}
    s_i(t) &= s_i(0) - \frac{1}{C_i} \int_0^t i_i(t) \, dt, \\
    p_i(t) &= V_i(t)i_i(t), \quad i \in \mathcal{N} = \{1, 2, \ldots, N\},
\end{align*}
\]

where \( s_i(t), s_i(0), C_i \) and \( i_i(t) \) are the SoC value, the initial SoC value, the capacity and the output current of the \( i \)-th battery unit, respectively. \( p_i(t) \) is the output power of the \( i \)-th battery unit. \( V_i(t) \) is the output voltage. Note that \( p_i < 0 \) indicates charging and \( p_i > 0 \) indicates discharging. In general, the output voltage \( V_i(t) \) of each unit is assumed to be unchanged during its operation [16]. Differentiating both sides of the first equation of (1) yields \( \dot{s}_i(t) = -\frac{1}{C_i}i_i(t), \ i \in \mathcal{N} \). Furthermore, one has \( \dot{s}_i(t) = -\frac{1}{C_i}P_i(t), \ i \in \mathcal{N} \). For each battery unit \( i \in \mathcal{N} \), define the battery unit state \( x_i(t) = C_iV_i(t) \) for discharging mode and \( x_i(t) = C_iV_i(1 - s_i(t)) \) for charging mode.

Moreover, the following assumption is made.

**Assumption 1** [10]: There exist constants \( a_1, a_2 > 0 \) such that \( a_1 \leq x_i(t) \leq a_2, t \geq 0, i \in \mathcal{N} \).

Denote the average battery unit state and the average desired power as, respectively, \( x(t) = \frac{1}{N} \sum_{i=1}^{N} x_i(t), p(t) = \frac{1}{N} \sum_{i=1}^{N} p_i(t) \), where \( p^* \) is total desired power.

In this brief, the following assumption on \( p^* \) is required.

**Assumption 2** [7], [10]: The total desired charging/discharging power \( P^* \) of BESSs satisfies \( P \leq |P^*| \leq \bar{P}, \ t \geq 0 \), \( |\dot{P}^*| \leq \epsilon, t \geq 0 \), where \( \bar{P}, P \), and \( \epsilon \) are positive constants.

In this brief, each battery unit is able to communicate with its neighbors, then the following assumptions on the communication topology of BESSs are made.

**Assumption 3** [7], [10]: The communication topology of BESSs is an undirected connected graph.

**Assumption 4** [10]: At least one but not all battery units have access to the total desired power \( p^* \).

From Assumptions 3 and 4, the matrix \( H = L + B > 0 \) [17], where the diagonal matrix \( B = \text{diag}(b_1, b_2, \ldots, b_N) \), \( b_i = 1 \) if the \( i \)-th battery unit gets access to the total desired power \( p^* \) and \( b_i = 0 \) otherwise.

The control objective of BESSs is stated as follows.

**Problem 1**: Consider BESSs (1), assume that Assumptions 1-4 hold. By using the local information, design the SoC balancing and the charging/discharging power tracking distributed controllers for the battery units so that

1) all battery units achieve SoC balancing with any pre-specified accuracy \( \varepsilon_s \geq 0, i.e., \lim_{t \to \infty} \|s_i(t) - s_j(t)\| \leq \varepsilon_s, i, j \in \mathcal{N} \);

2) the total charging/discharging power of BESSs tracks the total desired power with any pre-specified accuracy \( \varepsilon_p \geq 0, i.e., \lim_{t \to \infty} \| \sum_{i=1}^{N} p_i - p^*(t) \| \leq \varepsilon_p, i \in \mathcal{N} \).
III. POWER CONTROL BASED ON PRESPECIFIED-TIME OBSERVER

To solve Problem 1, the following control strategy is developed in [7].

\[ p_i(t) = x_i(t)(x_a(t) - p_a(t)). \]  

(3)

Note that both \( p_a(t) \) and \( x_a(t) \) are global information, which are not available to every battery unit. Recently, [10] introduced two types of distributed observers, one can achieve asymptotic estimation on \( p_a(t) \) and \( x_a(t) \), while the other ensures finite-time estimation. Unfortunately, the proposed distributed asymptotic observers in [10] can only be carried out as time tends to infinity, while the observer convergence rate of the distributed finite-time observers depends on the initial values of BESSs. In fact, the prespecified-time convergence property is more desirable. Motivated by [18], firstly, the following prespecified-time distributed observer is proposed to estimate \( p_a(t) \),

\[ \dot{\hat{p}}_{a,i} = -\alpha \text{sign}(v_i) - \psi \frac{r}{t_b - t_0} \omega(t)v_i, \]

\[ v_i = \sum_{j \in N_i} a_i(\hat{p}_{a,i} - \hat{p}_{a,j}) + b_i(\hat{p}_{a,i} - p_a), \]

where \( \hat{p}_{a,i} \) is the \( i \)-th battery unit’s estimation of \( p_a(t) \), \( \alpha, \psi \) and \( r \) are positive parameters, \( v_i \) is the internal state, the function \( \omega(t) \) is defined as: \( \omega(t) = \frac{\lambda_{\text{max}}(H^T)}{\lambda_{\text{min}}(H^T)} \) if \( t \in [t_0, t_b) \) and \( \omega(t) = 1 \) if \( t \in [t_b, \infty) \), where \( t_b \) is a prespecified time.

**Lemma 1:** Consider BESSs (1) with the prespecified-time distributed observer \( \hat{p}_{a,i} \). Assume that Assumptions 2-4 hold. Then, the average desired power \( p_a(t) \) can be estimated accurately at prespecified time \( t_b \), i.e., \( \hat{p}_{a,i}(t) = p_a(t) \) over \( t \in [t_b, \infty) \), if the observer parameter \( \alpha \) is selected such that \( \alpha \geq \frac{\epsilon}{\lambda_{\text{max}}(H^T)} \).

**Proof:** Denote \( \dot{\hat{p}} = (\hat{p}_{a,1}, \hat{p}_{a,2}, \ldots, \hat{p}_{a,N})^T \), \( \ddot{\hat{p}} = \dot{\hat{p}} - \hat{p}_a - 1_Np_a \), and \( \ddot{\hat{p}} = (\ddot{p}_1, \ddot{p}_2, \ldots, \ddot{p}_N)^T \), then it follows from (5) that \( v = L\dot{\hat{p}}_a + B\dot{p}_a - B1_Np_a = H\dot{\hat{p}}_a - H1_Np_a = H\ddot{p}_a \), where \( H = L + B \). Consider the Lyapunov function candidate \( V_1(t) = \frac{1}{2}v^T H^{-1}v \). Then, The time derivative of \( V_1(t) \) is evaluated as

\[ \dot{V}_1(t) = v^T H^{-1} \dot{\hat{p}} = v^T (\ddot{\hat{p}} - \hat{p}_a - 1_N \frac{1}{N} \ddot{p}^a) \]

\[ \leq -\alpha \sum_{i=1}^{N} |v_i| - \frac{\psi}{t_b - t_0} \omega(t) \sum_{i=1}^{N} v_i^2 \]

\[ - \sum_{i=1}^{N} \left( \ddot{p}_i + \hat{p}_a + 1_N \ddot{p}^a \right) \]

\[ \leq -\alpha \sum_{i=1}^{N} |v_i| - \frac{\psi}{t_b - t_0} \omega(t) \sum_{i=1}^{N} v_i^2 + \frac{\epsilon}{N} \|v\|^2 \]

\[ \leq (-\alpha + \frac{\epsilon}{N}) \|v\|^2 - \frac{\psi}{t_b - t_0} \omega(t) \|v\|^2 \]

\[ \leq \frac{\psi}{t_b - t_0} \omega(t) \|v\|^2 \]

\[ \leq \frac{2}{\lambda_{\text{max}}(H)} \|v\|^2 \]

by using the fact that \( \alpha \geq \frac{\epsilon}{\lambda_{\text{max}}(H^T)} \) and \( \frac{1}{2}v^T H^{-1}v \leq \frac{1}{2}v^T H^{-1}v \leq \frac{1}{2} \lambda_{\text{max}}(H^T) \|v\|^2 \).

Denote \( \Omega(t) = \omega(t) \), it gives that

\[ \frac{r}{t_b - t_0} \omega(t) = \frac{\Omega(t)}{\Omega(t)} \cdot \frac{\Omega(t)}{\Omega(t)}. \]

(7)

According to (6) and (7), it gets that

\[ V_1(t) \leq \left[ \omega(t) \right] - \frac{2\psi}{\lambda_{\text{max}}(H^T) \lambda_{\text{min}}(H^T)} \left[ \omega(t) \right] V_1(t_0). \]

(8)

Moreover, one from the definition of \( \omega(t) \) that \( \left[ \omega(t) \right] = \frac{1}{\lambda_{\text{min}}(H^T)} \left[ \omega(t) \right] \), which implies that \( \lim_{t \to t_b} \left[ \omega(t) \right] = 0 \). Therefore, \( \lim_{t \to t_b} \left[ \omega(t) \right] = 0 \), so does \( \lim_{t \to t_b} \| \dot{\hat{p}}_a \| = 0 \), that is, the average desired power \( p_a(t) \) is estimated accurately at prespecified time \( t_b \). Furthermore, for \( t \in [t_b, \infty) \), following the similar step in above, one obtains that

\[ V_1(t) \leq \frac{r}{t_b - t_0} \omega(t) \|v\|^2. \]

Since \( \omega \) is continuous, \( V_1(t) \) is also continuous. Therefore, \( \lim_{t \to t_b} V_1(t) = V_1(t_b) \). Then one can get

\[ 0 \leq V_1(t) \leq V_1(t_0) \leq 0, \]

which means that \( V_1(t) \equiv 0 \) on \( t \in [t_b, \infty) \), thus \( \dot{\hat{p}}_a \equiv 0 \) and \( \ddot{\hat{p}}_a \equiv 0 \) over \( t \in [t_b, \infty) \).

Lastly, the boundedness of the proposed observer over \([0, \infty) \) is checked.

Denote \( \psi_1 = \frac{\psi}{\lambda_{\text{min}}(H^T)} \), for \( t \in [t_0, t_b) \), it can deduce that

\[ \| \dot{\hat{p}}_a \| \leq \sqrt{\frac{2\lambda_{\text{max}}(H^T)}{\lambda_{\text{min}}(H^T)}} \| \omega(t) \| \| \dot{\hat{p}}_a \| \leq \sqrt{\frac{2\lambda_{\text{max}}(H^T)}{\lambda_{\text{min}}(H^T)}} \| \dot{\hat{p}}_a \|. \]

When \( \psi_1 r > 2 \), one has that

\[ 0 < \| \omega(t) \| \psi_1 r - 1 < 1 \]

and \( 0 < \| \omega(t) \| \psi_1 r - 1 < 1 \). Then

\[ \max \{ (\| \omega(t) \| \psi_1 r \|, \| \dot{\hat{p}}_a \|, \| \ddot{\hat{p}}_a \| \} \leq \frac{\lambda_{\text{max}}(H^T)}{\lambda_{\text{min}}(H^T)} \| \dot{\hat{p}}_a \|. \]

Moreover, it follows from (4) that \( \| \ddot{\hat{p}}_a \| \leq (\alpha + \frac{r}{t_b - t_0} \lambda_{\text{max}}(H^T)) \| \dot{\hat{p}}_a \| \), which confirms that \( \dot{\hat{p}}_a \) is bounded on \([0, t_b) \). Similarly, it can be seen from the definition that \( \ddot{\hat{p}}_a \) is bounded on \([t_b, \infty) \). This ends the proof.

For each battery unit \( i \in N \), to estimate \( x_a(t) \), the following prespecified-time battery unit average state observer is further constructed:

\[ \dot{\hat{x}}_i = -\beta \text{sign}(\hat{x}_i) - \psi \frac{r}{t_b - t_0} \omega(t) \hat{x}_i \]

(9)

\[ \hat{x}_i = \sum_{j=1}^{N} a_i(\hat{x}_{a,i} - \hat{x}_{a,j}) \]

(10)

\[ \hat{x}_{a,i} = \sum_{j=1}^{N} a_i(q_i - q_j) + x_i, \]

(11)

where \( \hat{x}_{a,i} \) is the estimate state of the \( i \)-th battery unit for \( x_{a,i} \), \( \beta \) is a positive parameter, \( \hat{x}_i \) and \( q_i \) are the internal states.

**Lemma 2:** Consider BESSs (1) with the prespecified-time distributed observer (11). Assume that Assumptions 1, 3 and 4 hold. Then, the average battery unit state \( x_a(t) \) can be estimated accurately at prespecified time \( t_b \), i.e., \( \hat{x}_{a,i}(t) = x_{a,i}(t) \) over \( t \in [t_b, \infty) \), if the observer parameter \( \beta \) is selected such that \( \beta \geq \frac{\prod}{\sqrt{\lambda_{\text{max}}(H^T)}} \).
Proof: Denote \( \hat{x}_a = (\hat{x}_{a,1}, \hat{x}_{a,2}, \ldots, \hat{x}_{a,N})^T \), \( \hat{x} = \hat{x}_a - x_a 1_N \) and \( \hat{\xi} = (\hat{\xi}_1, \hat{\xi}_2, \ldots, \hat{\xi}_N)^T \); then one can obtain that
\[
\dot{\hat{\xi}} = \hat{\xi}_a - \dot{x}_a 1_N = L \dot{\xi} + \hat{\xi} - \dot{\xi}_a 1_N
\]
\[
= L \dot{\xi} + L \hat{\xi} \dot{x} + \hat{\xi}^{-} 1_N \dot{x}_a
\]
where \( L^T \) is the generalized inverse matrix of \( L \).

Consider the Lyapunov function candidate \( V_2(t) = \frac{1}{2} \hat{\xi}^T \hat{\xi} \).

The derivative of \( V_2(t) \) along the trajectory of (12) is evaluated as
\[
\dot{V}_2(t) = \frac{1}{2} \dot{\hat{\xi}}^T \hat{\xi} + \frac{1}{2} \hat{\xi}^T L \dot{\xi} + \frac{1}{2} \hat{\xi}^T L \hat{\xi} \dot{x} + \hat{\xi}^T \hat{\xi} \frac{1}{2} \dot{x}_a 1_N^T \hat{x}
\]
\[
= \dot{\xi}^T L \dot{\xi} + \hat{\xi}^{-T} 1_N \dot{x}_a 1_N^T \hat{x}
\]
where \( \hat{\xi}^{-} 1_N \dot{x}_a 1_N ^T \hat{x} \) is non-negative. This ensures the stabilization of the system.

Remark 1: In contrast to the asymptotic observers/finitetime observers employed in [10], the prespecified-time observers are proposed herein. The novelty of those observers lies in the fact that they are able to handle the prespecified-time observers accurately, and the prespecified-time observers are designed to achieve the prespecified-time stabilization of the corresponding estimation error systems. This ends the proof.

Remark 2: Unlike [10], [15], where both the asymptotic observers and the finite-time observers are proposed, respectively, two novel prespecified time observers are constructed in our work. It is worth noting that the settling time of the prespecified-time observers [10], the finite-time observers [10] and the fixed-time observers [15] is infinity, depends on both the initial states of BESSs, and related to the parameter of the control strategy, respectively, while the settling time of the observers (4) and (9) is determined in advance according to task requirement and independent of the initial states and parameters of the control strategies.

Remark 3: It should be pointed out that the potential drawback of the prespecified-time observer-based power control strategy proposed in this brief is that the utilized control method implements in the sense of asymptotical convergence. How to construct a suitable power control strategy with finite-time [14], fixed-time [14], [19], [20], [21] or prespecified-time convergence and how to deal with communication constraints [22], [23] deserve further investigation in future work.

IV. Simulation Examples

Example 1: Consider the following BESSs with 6 battery units, the parameters of the battery units are \( V = 20V \), \( C = 220Ah \), and the initial SoC of the battery units are \( 0.95, 0.86, 0.83, 0.93, 0.97, 0.88 \). The communication topology of BESS is shown in Fig. 1. Assume that only battery unit 1 has access to the desired charging/discharging power, i.e., \( b_1 = 1 \), and \( b_i = 0, i = 2, 3, \ldots, 6 \). Moreover, assume that the desired power is given as follows:

1) Case 1: \( p^*(t) = \pm(4200 \sin(t) + 4200) W \).
2) Case 2:

\[
p^*(t) = \pm\begin{cases} 
1000W & \text{if } t \in [0, 0.25), \\
1500\sin(5t) + 2000W & \text{if } t \in [0.25, 0.5), \\
5000W & \text{if } t \in [0.5, 0.75), \\
-4000W + 6000W & \text{if } t \in [0.75, 1]. 
\end{cases}
\]
For the prespecified-time distributed observers, the prespecified time is chosen as $t_0 = 4$ and $t_0 = 0$. According to Lemmas 1 and 2, the observer parameters are selected as $\alpha = 1000$, $\beta = 3430$. According to $\frac{\psi \lambda_2(L^TL)}{\lambda_{\text{max}}(H-1)} > 2$ and $\psi \lambda_2(L^TL)r > 2$, the observer parameters are selected as $\psi = 1$, $r = 50$. The initial states of the observers (4) and (9) are given as $v_i(0) = 0$, $\hat{p}_i(0) = p_i(0) = 0$, $q_i(0) = 0$, $\dot{x}_i(0) = \chi_i(0)$, $i = 1, 2, \ldots, 6$. Then, the simulation results under different methods are shown in Fig. 2 and Fig. 3, where the solid line represents the simulation results under our control method, the dotted line represents that in [10], and the thickened solid line represents the desired power $p^*$. It can be observed that the proposed cooperative control method is better than that in [10] and [15].

V. CONCLUSION

This brief has investigated the problem of SoC balancing and power tracking control for BESSs with multiple heterogeneous battery units. Two prespecified-time distributed observers have been constructed to estimate the average desired power and the average battery unit state, respectively. Then, the effectiveness of the prespecified-time distributed observers based control strategy has been further analyzed theoretically and verified by several simulation examples. Future works include extending this results to distributed control of BESSs with time delays or communication constraints.

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