2023 IEEE the 7th Conference on Energy Internet and Energy System Integration

Consensus-based Coordination of Battery Energy Storage Systems for Frequency Regulation Service

Hongyi Li
State Key Laboratory of Internet of Things for Smart City
University of Macau
Macao, China
hongyi.li@connect.um.edu.mo

Hongxun Hui
State Key Laboratory of Internet of Things for Smart City
University of Macau
Macao, China
hongxunhui@um.edu.mo

Hongcai zhang
State Key Laboratory of Internet of Things for Smart City
University of Macau
Macao, China
hczhang@um.edu.mo

2023 IEEE 7th Conference on Energy Internet and Energy System Integration (EI2) | 979-8-3503-4509-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/EI259745.2023.10513161

***Abstract*—Battery energy storage systems (BESSs) have been widely adopted in providing ancillary services, e.g., frequency regulation, to the power system. Existing studies usually focus on the accurate tracking of regulation signal, while overlook the heterogeneous cost in actuating different BESS units, which might lead to a less cost-efficient operation. In this paper, we present a convex optimization model to describe the cost-aware power allocation problem of BESSs in tracking regulation signal. Considering privacy protection and scalability, we propose a consensus-based algorithm for BESS coordination in a fully-distributed manner. The optimal power allocation among BESSs is achieved by exchanging auxiliary variables within the local neighborhood, which protects the privacy and promotes the scalability. Several numerical experiments are presented to show the effectiveness of the proposed method. The optimal power allocations in individual time intervals are validated, and the collective tracking performance of the BESS units is illustrated. The economic benefit of the cost-aware power allocation strategy is also demonstrated in the case study.**

***Index Terms*—battery energy storage systems, consensus-based algorithm, distributed optimization, frequency regulation.**

I. Introduction

The paradigm shift to a low-carbon power system leads to the prevalence of renewable energy sources in the power grid [1]. The intermittent and uncertain nature of the power output of the renewable generators brings great challenge to the dynamic supply-demand balance of the power system [2]. The mismatch of power supply and demand could result in severe deviation of the system frequency, which is undesirable in the power system [3]. Thus, to maintain the system frequency within the acceptable range, frequency regulation services are essential to the power grid.

Traditionally, frequency regulation services are provided by synchronous generators, e.g., coal plants [4]. However, these generators need to run part-loaded [5]. Moreover, conventional synchronous generators are fading away due to the decarbonization of the power system. Thus, as the alternative, the application of distributed energy resources in frequency regulation has been widely studied [6]. Among different types of distributed energy resources, the battery energy storage system (BESS) is regarded as an ideal resource for frequency regulation, due to its fast response rate and large instantaneous power [7].

Since the provision of frequency regulation services usually involves numerous BESSs, centralized control schemes suffer from some critical issues, such as heavy computational burden, signal point of failure and privacy leakage [8]. Many researchers study the distributed control frameworks of BESSs for frequency regulation. Datta *et al.* [9] propose a coordinated control framework for BESSs to mitigate the frequency deviation resulting from the fluctuation of renewable energy generation. Zhong *et al.* [10] improve of the frequency stability of power system by co-dispatching BESSs and traditional frequency regulation resources. Zhang *et al.* [11] study the cooperation of BESSs and conventional generators in frequency regulation. Zhao *et al.* [12] propose a primary control strategy for BESSs to regulate both frequency and voltage of a microgrid. These studies focus on promoting the accurate tracking of regulation signal. However, the heterogeneity in the cost of different BESS units is not considered, which might lead to a less cost-effective BESS power dispatching result.

Considering the heterogeneous cost functions of BESSs, Zhao *et al.* [13] depict the operation cost of BESS units with a convex function and propose a power allocation strategy with minimum cost. Ma *et al.* [14] investigate the impact of life cycle on the operation cost of BESSs, and study the optimal power allocation of BESSs to provide frequency regulation services in the Pennsylvania-New Jersey-Maryland Interconnection (PJM) market. In the PJM market, flexible resources like BESSs can contribute to the frequency regulation of the system by adjusting their power according to the RegD signal sent by the market. Anderson *et al.* [15] study the optimal coordination of multiple distributed energy resources, including BESSs, to track the RegD signal in PJM market. As individual units, the BESSs would value their cost functions and operational limits as private information. Thus, the privacy-preserving algorithm for the optimal power allocation considering cost heterogeneity needs to be studied.

As a fully-distributed algorithm with a privacy-preserving feature, the consensus-based algorithm is widely applied in

This paper is funded in part by the Science and Technology Development Fund, Macau SAR (File no. SKL-IOTSC(UM)-2021-2023, and File no. 0011/2021/AGJ) and in part by the Zhuhai Science and Technology Innovation Bureau (File no. ZH22017002210007PWC).

the power system operation [16], e.g., economic dispatch [17] and optimal power flow [18]. Instead of sharing private information, the consensus-based algorithms solve the optimization problem by exchanging the values of auxiliary variables, which avoids the privacy leakage issue [19]. Although the consensus-based algorithm is a good candidate for BESS coordination to provide frequency regulation services, to the best knowledge of the authors, few research works are reported in the literature.

In this paper, we propose a fully-distributed coordination method for BESSs providing frequency regulation service. Considering the heterogeneous costs of BESSs, we first model the optimal coordination of BESSs as a convex and separable optimization problem. Based on the optimization model, we propose a consensus-based algorithm to solve the problem in an iterative, interactive and privacy-preserving manner. Numerical experiments are presented to show the effectiveness of the proposed method in achieving optimal power allocation among BESS units. Compared with rule-based methods, the advantage brought by considering heterogeneous costs is also discussed in the case study section.

The remainder of this paper is organized as follows: Section II introduces the optimization model for BESS coordination. Section III presents the consensus-based algorithm to solve the optimization problem. Numerical experiments are included in Section IV, and Section V concludes the paper.

II. Problem Formulation

A. Terms and Notations

Before introducing the optimization model of coordinating a BESS fleet for frequency regulation service, we first introduce some terms and notations. Following the convention of literature about fully-distributed coordination, we term the BESSs as *agents* throughout the remainder of this paper. With the wide application of smart grid technology, for flexible resources, e.g., BESSs, the information exchange with other resources becomes an essential function of the end controllers. Thus, without losing generality, in this paper, we assume that there exist an undirected communication topology between BESSs, where BESS units can exchange information with their communication neighbors. Defining the set of all agents as $\mathcal{I}$, we model the communication topology between BESSs as a graph $\mathcal{G} = \{\mathcal{I}, \mathcal{E}\}$, where the set of edges, $\mathcal{E}$, represents the set of communication links. For a communication link between agent i and agent j, we have $(i,j) \in \mathcal{E}$ and $(j,i) \in \mathcal{E}$. The set of communication neighbors of agent i is denoted by $\mathcal{N}_i = \{j|(i,j) \in \mathcal{E},\ i \neq j\}$. Denoting the cardinality of a set with $|\cdot|$, the number of communication neighbors of agent i is $|\mathcal{N}_i|$. The agents and their communication neighbors are indexed by i and j. We use k as the index of iterations, and t as the index of time intervals. The length of each time interval is denoted by Δt.

B. Optimization Model

To keep a compact mathematical formulation, in this paper, we use only one variable $P_{i,t}$ to denote the power of BESS i at time interval t. We define that during time interval t, BESS i charges when $P_{i,t} > 0$, and discharges when $P_{i,t} < 0$. We also assume that the BESS units only charge/discharge to participate in frequency regulation. At time interval t, for a BESS fleet, the problem of collectively tracking the frequency regulation signal can be formulated as follows:

$$\min_{P_{i,t}, i\in\mathcal{I}} \sum_{i\in\mathcal{I}} C_i\left(P_{i,t}\right) \tag{1a}$$

$$\text{s.t.} \sum_{i\in\mathcal{I}} P_{i,t} = P_t^{\text{ref}}, \tag{1b}$$

$$P_{i,t}^{\min} \le P_{i,t} \le P_{i,t}^{\max}, \tag{1c}$$

where $P_{i,t}$ is the power of BESS i at time interval t; $C_i(\cdot)$ is the cost function of BESS i; P_t^{ref} is the regulating power of the BESS fleet; $P_{i,t}^{\max}$ and $P_{i,t}^{\min}$ are the maximum charging/discharging powers of BESS i at time t. The calculation of P_t^{ref} is discussed in the next subsection. Problem (1) aims to minimize the cost of actuating BESSs for frequency regulation service provision, without violating the physical limits.

Based on Ref. [13], we make the following assumptions on the cost functions $C_i(\cdot)$:

1) Convexity: the per unit power loss and degradation cost increase as the power of BESS increases, i.e., $C_i^{''}(P_{i,t}) > 0, \forall i \in \mathcal{I}$, where $C_i^{''}(P_{i,t})$ is the second-order derivative of $C_i(\cdot)$ with respect to $P_{i,t}$.
2) Non-negative: the cost of actuating BESS units for both charging and discharging is non-negative, i.e., $C_i(P_{i,t}) \ge 0, \forall P_{i,t} \in [P_{i,t}^{\min}, P_{i,t}^{\max}], \forall i \in \mathcal{I}$.
3) Zero-crossing: the operation cost of the BESS unit is zero it is idle, i.e., $C_i(0) = 0, \forall i \in \mathcal{I}$.

In this context, problem (1) is a convex optimization problem with affine constraints, of which there exist a unique global optimal solution.

The charging/discharging power of BESS i at time t will affect the amount of energy stored in BESS i at time $t+1$:

$$E_{i,t+1} = \begin{cases} E_{i,t} + \xi_i^{\text{char}} P_{i,t} \Delta t, P_{i,t} \ge 0, \\ E_{i,t} + \frac{P_{i,t}}{\xi_i^{\text{disc}}} \Delta t, P_{i,t} < 0, \end{cases} \tag{2}$$

where $E_{i,t}$ is the energy stored in BESS i at time t; ξ_i^{char} and ξ_i^{disc} are the charging and discharging efficiency parameters of BESS i, which are assumed to be constant.

Assuming that the power of BESS remains constant during the time interval, the power limits of BESS i at time interval $t+1$ can be calculated by:

$$P_{i,t+1}^{\max} = \min\left(P_i^{\text{charge}}, \frac{E_i^{\max} - E_{i,t}}{\Delta t}\right), \tag{3}$$

$$P_{i,t+1}^{\min} = \max\left(P_i^{\text{discharge}}, \frac{E_i^{\min} - E_{i,t}}{\Delta t}\right), \tag{4}$$

where P_i^{charge} and $P_i^{\text{discharge}}$ are the maximum charging/discharging powers of BESS i, respectively; $E_i^{\max}$ and $E_i^{\min}$ denote the upper and lower energy limits of BESS i.

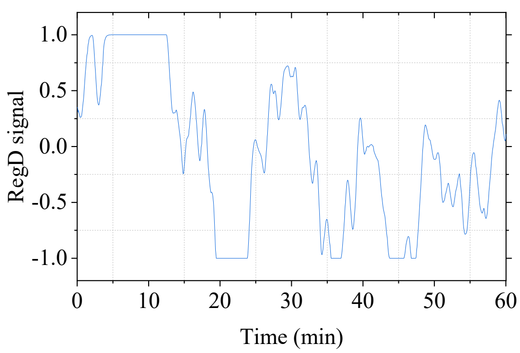


Fig. 1. The RegD signal in PJM market sent to the regulating resources, from 00:00 to 01:00, August 2, 2020.

C. Regulation Signal

Frequency regulation services usually involve both upward and downward regulation, implying that the BESSs should either discharge to inject power to the grid or charge to draw power from the grid. The regulation signal γ_t ranges from -1 to 1, i.e., $\gamma_t \in [-1, 1]$. In this paper, we define that when $\gamma_t > 0$, the BESSs are required to charge at time interval t, while $\gamma_t < 0$ indicates that the BESSs are required to discharge. Assuming that the BESS fleet bid in the market with whole capacity $P_{\text{cap}}^{\text{BESS}}$, we have$P_t^{\text{ref}} = \gamma_t P_{\text{cap}}^{\text{BESS}}$. In the PJM market, the RegD signal is generated by the market operator based on the area control error of the power system in a two-second scan rate, i.e., $\Delta t = 2s$, as illustrated in Fig. 1. The flexible resources, e.g., BESSs, need to adjust their power according to the signal. However, there is no requirement to consider the frequency dynamic of the power system. Thus, in this paper, we focus on the optimal power allocation among BESS units with a given regulation signal, while the system frequency is not included in the model.

III. Proposed Consensus-based Algorithm

In this section, we first introduce the classical primal-dual iterative method in solving problem (1), which serves as the basis of our proposed consensus-based algorithm. The partial Lagrangian dual of objective function (1a) can be written as:

$$\mathcal{L}\left(\boldsymbol{P_t}, \lambda\right) = \sum_{i \in \mathcal{I}} C_i(P_{i,t}) + \lambda_t \left(P_t^{\text{ref}} - \sum_{i \in \mathcal{I}} P_{i,t} \right), \tag{5}$$

where $\boldsymbol{P_t}$ is a vector with $P_{i,t}, \forall i \in \mathcal{I}$ as its elements; λ_t is the Lagrangian multiplier corresponding to equation (1b) at time t, of which the absolute value can be interpreted as the incremental cost of actuating BESSs.

In the primal-dual method, λ_t is updated iteratively:

$$\lambda_t(k+1) = \lambda_t(k) + \eta \zeta_t(k), \tag{6}$$

$$\zeta_t(k) = P_t^{\text{ref}} - \sum_{i \in \mathcal{I}} P_{i,t}(k), \tag{7}$$

where $\zeta_t(k)$ is the mismatch between the target regulating power and the sum of scheduled regulating power at iteration k. With the updated λ_t, the power schedule of each BESS is updated following:

$$\begin{aligned} P_{i,t}\left(k+1\right) = \underset{P_{i,t}}{\text{argmin}} \;\; & C_i\left(P_{i,t}\right) - \lambda_t\left(k+1\right) P_{i,t}, \\ \text{s.t.} \;\; & P_{i,t}^{\min} \leq P_{i,t} \leq P_{i,t}^{\max}. \end{aligned} \tag{8}$$

By executing equations (6)-(8), the optimal solution of problem (1) can be obtained [20]. The rationale behind equations (6) - (8) can be explained from a microeconomic point of view. Based on equation (7), we interpret $\zeta_t(k)$ as the net shortage of charging power at iteration k. A positive $\zeta_t(k)$ drives the value of $\lambda_t(k)$ to increase, i.e., more incentives are provided. When $P_t^{\text{ref}} > 0$, increasing incentives motivate the BESSs to increase charging power. Similarly, when $P_t^{\text{ref}} < 0$, a negative $\zeta_t(k)$ drives the value of $\lambda_t(k)$ to decrease, motivating the BESSs to provide more discharging power. Thus, as the algorithm iterates, the value of ζ_t will gradually converge to zero, implying that the value of λ_t and the power scheduling of BESSs reach a steady state.

Remark 1: When $P_t^{\text{ref}} > 0$, the optimal solution to problem (1) will satisfy $P_{i,t}^* > 0, \forall i \in \mathcal{I}$. In this scenario, λ_t^* will be positive and can be naturally interpreted as the incremental cost of actuating BESSs for frequency regulation. However, when $P_t^{\text{ref}} > 0$, λ_t^* will be negative, since $P_{i,t}^* < 0, \forall i \in \mathcal{I}$. In this scenario, the incremental cost of BESS actuation is equal to the absolute value of λ_t^*, i.e., $|\lambda_t^*|$.

The main hurdle of applying the above algorithm in the decentralized solving of problem (1) is that the calculation of equations (6) and (7) involves global information, i.e., λ_t and ζ_t, which are inaccessible for individual agents. To tackle this issue, in the proposed consensus-based algorithm, we introduce two local variables, $\lambda_{i,t}$ and $\zeta_{i,t}$, to represent the estimations of global information made by agent i. The proposed consensus-based algorithm is shown in Algorithm 1.

Algorithm 1 solves problem (1) in an iterative and interactive manner. Equation (10) calculates the weighted average of the estimations of incremental cost made by agent i and its communication neighbors. According to equation (5), ζ_t is the gradient direction of $\mathcal{L}$ with respect to λ_t. Thus, the last term of equation (10) guides the local estimations of λ_t to the optimal value based on the local estimation of ζ_t. Similarly, equation (12) calculates the weighted average of the local estimations of power mismatch, and adjusts the local estimation with the optimal response to the updated $\lambda_{i,t}$. Collectively, equations (10) and (12) guide the agents to approach the global optimum of problem (1).

Remark 2: In Algorithm 1, the agents only exchange their estimations about price and power mismatch, i.e., $\lambda_{i,t}$ and $\zeta_{i,t}$, which are auxiliary variables. Privacy information, e.g., $C_i(\cdot)$, $P_{i,t}^{\max}$ and $P_{i,t}^{\min}$, are only used in local computation. Thus, the proposed algorithm protects the privacy information of BESS units in the process of solving problem (1).

IV. Case Study

In this section, we present several experiments, which demonstrate the effectiveness of the proposed consensus-based

Algorithm 1 Proposed Consensus-Based Algorithm

Initialization:

The initial power generation/consumption $P_{i,t}(0)$ can be set to any value within the range $\left[P_i^{\min}, P_i^{\max}\right]$. The rest of the variables are initialized as follows:

$$\lambda_{i,t}(0) = C_i'\left(P_{i,t}(0)\right), \zeta_{i,t}(0) = P_{i,t}^{\text{ref}} - P_{i,t}(0), \quad (9)$$

where $C_i'(\cdot)$ is the first-order derivative of $C_i(\cdot)$; the local information $P_{i,t}^{\text{ref}}$ satisfies $\sum_{i\in\mathcal{I}} P_{i,t}^{\text{ref}} = P_t^{\text{ref}}$, which requires at least one agent to have access to P_t^{ref}.

Iteration:

Step 1 **(Update price estimation):** Update $\lambda_{i,t}$ following:

$$\lambda_{i,t}(k+1) = \sum_{j\in\mathcal{N}_i\cup i} w_{ij}\lambda_{j,t}(k) + \eta\zeta_{i,t}(k), \quad (10)$$

where the weights are defined as:

$$w_{ij} = \begin{cases} \frac{1}{|\mathcal{N}_i|+1}, & \forall j \in \mathcal{N}_i \cup i, \\ 0, & \text{otherwise}. \end{cases} \quad (11)$$

Step 2 **(Optimal response):** Update $P_{i,t}$ with equation (8).

Step 3 **(Update power mismatch estimation):** Update $\zeta_{i,t}$ following:

$$\zeta_{i,t}(k+1) = \sum_{j\in\mathcal{N}_i\cup i} b_{ij}\zeta_{j,t}(k) + P_{i,t}(k) - P_{i,t}(k+1), \quad (12)$$

where the weights are defined as:

$$b_{ij} = \begin{cases} \frac{1}{|\mathcal{N}_j|+1}, & \forall i \in \mathcal{N}_j \cup j, \\ 0, & \text{otherwise}. \end{cases} \quad (13)$$

Step 4 **(Termination check):** the terminating criteria are:

$$\|\lambda_{i,t}(k+1) - \lambda_{i,t}(k)\| \le \epsilon_\lambda, \quad (14)$$

$$\|\zeta_{i,t}(k+1) - \zeta_{i,t}(k)\| \le \epsilon_\zeta, \quad (15)$$

where ϵ_λ and ϵ_ζ are the terminating thresholds for $\lambda_{i,t}$ and $\zeta_{i,t}$, respectively. If the above equations are satisfied, terminate the algorithm and take $P_{i,t}(K)$ as the obtained solution. Otherwise, let $k = k+1$ and return to ***Step 1***.

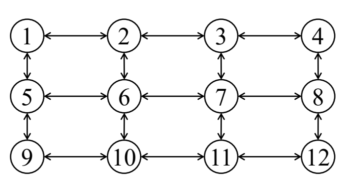
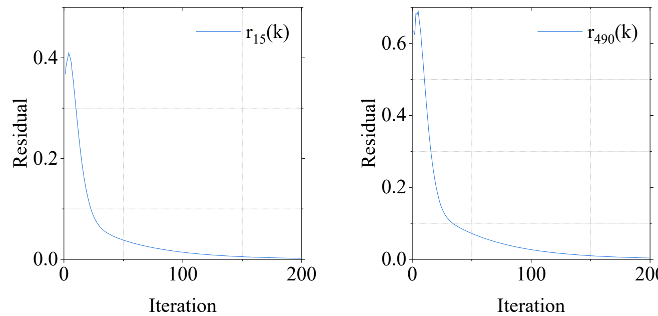


Fig. 2. Communication topologies of the BESS fleet.

algorithm and the impact of initialization strategy on the obtained solution, given that the maximum iteration number is limited. We simulate the coordination of 12 BESSs with the communication topologies in Fig 2, which is commonly used in multi-zone communications [21].



(a) Time interval 15. (b) Time interval 490.

Fig. 3. Solving results of two representative time intervals.

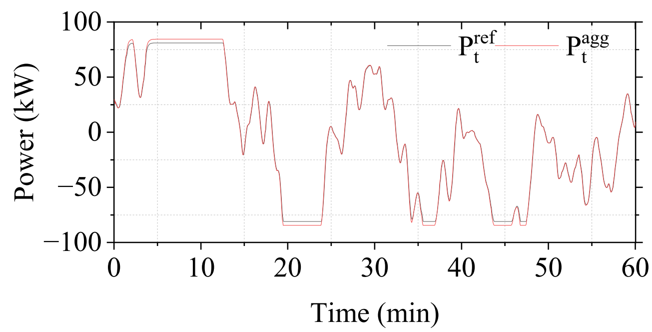


Fig. 4. Performance of the BESS fleet in collectively tracking RegD signal.

A. Effectiveness of Proposed Consensus-based Algorithm

We first verify that the proposed method, i.e., Algorithm 1, can obtain the global optimal solution of problem (1) in individual time intervals. In the first hour of Aug 2nd, 2020, there are 1800 time intervals. We select two representative time intervals, namely time interval 15 and time interval 490, where $P_{15}^{ref} > 0$ while $P_{490}^{ref} < 0$. Denoted by $\boldsymbol{P}_t^*$, the optimal solution obtained by GUROBI optimization solver [22] is used as the benchmark. With $\boldsymbol{P}_t(k) = \{P_{i,t}(k), \forall i \in \mathcal{I}\}$, the residual of iteration k is defined as:

$$r_t(k) = \|\boldsymbol{P}_t(k) - \boldsymbol{P}_t^*\|, \quad (16)$$

where the residual $r_t(k)$ is the Euclidean distance between the current solution and the optimum. When $r_t(k)$ reaches zero, the obtained solution is the optimal solution of problem (1).

In the case study, we assume that agent 1 accesses P_t^{ref}, i.e., $P_{1,t}(0) = P_t^{\text{ref}}$. For the rest of agents, $P_{i,t}(0) = 0$. The results of solving problem (1) in time interval 15 and time interval 490 are shown in Fig 3. In both time intervals, as Algorithm 1 iterates, the residual converges to zero, implying that the proposed algorithm can achieve the optimal power allocation among BESSs.

After verifying that the proposed algorithm can obtain the optimal power allocation in a single time interval, we investigate the performance of the BESS fleet in collectively tracking the RegD signal in one hour. Summing up the power

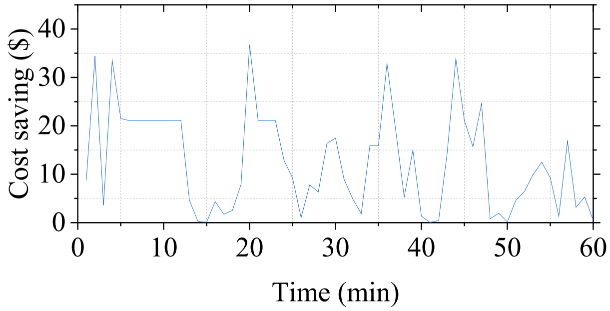


Fig. 5. Cost saving by optimally allocate the regulating power among BESS units.

of individual BESSs, we focus on the aggregated power of the BESS fleet:

$$P_t^{\text{agg}} = \sum_{i \in \mathcal{I}} P_{i,t}(K). \tag{17}$$

The results of running Algorithm 1 over a one-hour horizon is shown in Fig. 4. The overall performance of the BESS fleet on tracking the RegD signal is satisfactory. Although there exist a gap between P_t^{ref} and P_t^{agg} in some time intervals, the performance score of the BESS fleet reaches $S = 0.9852$, according to the calculation methods provided in the PJM manual [23]. Thus, we conclude that our proposed method can effectively coordinate the BESS units to provide frequency regulation services collectively.

B. Economic Benefit of Cost-aware Power Allocation

In the previous section, we demonstrate that the proposed algorithm can obtain the optimal power allocation among BESSs considering cost heterogeneity and the aggregated power of the BESS units tracks the regulation signal with a satisfactory accuracy. Based on this premise, the economic benefit brought by the cost-aware power allocation strategy is illustrated. The overall costs of actuating BESS units are compared between the proposed method and a rule-based method, which evenly distribute the regulating power among BESSs. The cost saving in each minute is shown in Fig. 5. With a higher regulating power, the cost saving brought by the proposed method becomes more significant, indicating the advantage of the proposed algorithm over conventional rule-based methods.

V. Conclusion

The increasing penetration of renewable energy resources stimulates the participation of distributed energy resources in providing frequency regulation services. In this paper, we propose a consensus-based method to coordinate a group of BESS for frequency regulation. A convex optimization model is first formulated, which paves the way to the design of the proposed algorithm. On the basis of primal-dual decomposition method, we propose a consensus-based algorithm that can coordinate the BESSs to provide both upward and downward frequency regulation services. Since the proposed algorithm only requires the information exchange of auxiliary variables within local communication neighborhoods, the private information of BESS units are well-protected. Taking the RegD signal in the PJM market as an example, we verify the effectiveness of the proposed algorithm with multiple experiments. Firstly, the proposed algorithm can optimally allocate the regulating power to BESS units, considering their heterogeneity in cost functions. The performance of the BESS fleet in collectively tracking the RegD signal is also demonstrated, of which the performance score reaches a satisfactory level. The economic benefit of the cost-aware power allocation strategy is also illustrated. When the required regulating power is large, the cost saving brought by the proposed method is more significant, implying its superiority over conventional rule-based methods.

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