Optimization-Based Ramping Reserve Allocation of Aggregated BESS for AGC Enhancement

Yiqiao Xu, Student Member, IEEE, Alessandra Parisio, Senior Member, IEEE, Zhongguo Li, Member, IEEE, Zhen Dong, Member, IEEE, and Zhengtao Ding, Senior Member, IEEE

Abstract—This paper considers Automatic Generation Control (AGC) enhancement by exploring the synergy between conventional generators and an aggregated Battery Energy Storage System (BESS). In practice, it has been observed that BESSs sometimes inefficiently contribute to the minimization of Area Control Error (ACE). This phenomenon is open to several interpretations. On the one hand, cost-effective aggregation of BESSs has not been well-established. On the other hand, BESSs could be driven into an inefficient operation due to miscalculated ACE. Moreover, some BESSs may have to operate in the opposite direction than desired to maintain energy neutrality. Therefore, this paper presents a novel scheme termed Optimization-based Ramping Reserve Allocation (ORRA) for BESS aggregation, addressing the three issues simultaneously. The underlying methodology is to formulate the BESS aggregation problem as an distributed online optimization problem and solve it in real-time, where corrected ACE is leveraged to quantify the instantaneous ramping requirements. Another distinctive feature of ORRA lies in its ability to immediately deploy and smoothly un-deploy the aggregated BESS with respect to a frequency event, thereby contributing to energy-neutral operation. The optimization algorithm is fully distributed and can guarantee fair and near-optimal allocation in real-time. Simulations on a modified IEEE 14-bus system are performed to illustrate the effectiveness of ORRA.

Index Terms—Battery Energy Storage System, Automatic Generation Control, Distributed Optimization.

I. INTRODUCTION

THE ambitious aim of replacing coal-based generation with Renewable Energy Sources (RESs) has aggravated the burden on frequency regulation due to immature management of RESs [1], [2]. Recognizing the operational challenges faced by existing power systems, policymakers and Independent System Operators (ISOs) around the world have actively engaged in the commercial use of Battery Energy Storage Systems (BESSs) in the provision of grid services. Automatic Generation Control (AGC) is a balancing mechanism at the secondary control layer to cover net-load forecasting errors, which has the ultimate goal of minimizing Area Control Error (ACE) [3]. As various studies [4]–[6] have demonstrated, a reasonably sized BESS is able to improve AGC performance and mitigate the pressure on Conventional Generators (CGs) in recognition of two facts. First, the CG cannot switch directions instantly in response to a new dispatch target. Second, the BESS can provide symmetric support and thus be re-dispatched faster in both directions.

An utility-scale BESS is normally composed of hundreds of battery modules in series and/or parallel. Over the decades, many utility-scale BESS projects with AGC functions have been commissioned, and there is a trend of aggregating geo-distributed BESSs as a large entity via a communication network to give substantial flexibility for utility applications [7], [8]. For example, Southern California Edison installed a 10 MW BESS and another 8 MW BESS at different transmission substations [4]. In Germany, an aggregated capacity of 90 MW/30 min BESS was equally distributed at six sites, each assigned a capacity of 15 MW [9]. However, it has been observed in some markets that BESSs are not always possible to efficiently minimize the ACE but sometimes give rise to counterproductive regulation [10]. This issue may result from three challenges, which primarily motivate our study in this paper:

1) Energy Neutrality: This is a concept requesting the cumulative energy input of a BESS to equal its cumulative energy output. Despite its significant and widely perceived importance to operating integrity, energy neutrality was not taken as seriously as it should have been in many studies [11]–[15]. As a consequence, some BESSs may have to move in opposition to what we expect for regulation to recover State-of-Charge (SoC) [16], or need to include a comprehensive SoC control such that the BESS acts only during designated periods [4]. In this regard, PJM turned the ACE into a RegA signal for CGs and a RegD signal for fast ramping resources with a calculation frequency of 2 seconds. The “hard-neutrality” imposed on the RegD signal kept the BESS from being over-charged or over-discharged but may force a considerable amount of RegD resources to act in the opposite direction of RegA resources [17]. Since 2017, PJM has switched to the conditional neutrality controller, a hybrid PID controller with an internal feedback loop that allows the RegD signal to be not strictly neutral but has a slight bias [18]. Midcontinent ISO (MISO) introduced a different scheme known as AGC enhancement, which places a priority on fast ramping resources in AGC and, more importantly, un-deploys them once the system frequency restores to the nominal value [19]. Compared to deliberately designing energy-neutral signals, this option directly utilizes the ACE and can make better use of the ramping capabilities of BESSs.

2) Bias Uncertainty: BESSs could be misled by miscalculated ACE and, in turn, hedge against the ACE control. It is not uncommon due to a frequently seen discrepancy between frequency bias $B$ and Area’s Frequency Response Characteristic $\beta$ (AFRC), which we term bias uncertainty. $\beta$
is determined as a combination of the governor droop $R^{-1}$ and the load damping factor $D$. Clearly, if CGs do not strictly adhere to the governor droop as specified, possibly attributed to governor-turbine nonlinearity, this will lead to a miscalculation of ACE. However, there is a contradiction arising in practice that $B$ updated on a yearly basis [20] while $\beta$ tends to be highly dynamic and frequency-coupled. In particular, $D$ can vary with frequency conditions substantially when there are a large number of controllable frequency-responsive resources (FRRs) [21]. Even a static bias uncertainty at 5% can have non-negligible impacts on settling time and cause unintended interaction between control areas [22]. Recently, the concept of Area Injection Error (AIE) has been proposed in [23], which corrects the ACE by removing the bias uncertainty manifested as turbine-governor nonlinearity, yet bias uncertainty from the load side remains unresolved. Thus, targeted processing of various bias uncertainty can be necessary.

3) Resource Allocation: Achieving the full potential of aggregated BESS to benefit AGC is still an open challenge. This is partly due to the lack of explicit instructions on how much each BESS should contribute to AGC, whereas uncoordinated decision made by service providers is naturally self-interest [10]. Traditional AGC systems usually adopt a proportional-based allocation, which cannot guarantee the optimality therein [24]. On this point, a variety of optimization-based strategies have been proposed in recent research, based on Model Predictive Control (MPC) [11], [12], Approximate Dynamic Programming (ADP) [13], and Deep Reinforcement Learning (DRL) [14], [25]. DRL needs to be pre-trained with massive data and then deployed online (quite often, DRL has low sampling efficiency and poor adaptiveness to changing environments, e.g., weather). ADP and MPC can be directly implemented online but may require extensive computational power, especially when their prediction horizon is large. In contrast, online optimization is promising for real-time implementation since it requires notably less computational time for each iteration [26]. In [27], an online optimization policy is tailored for BESS to optimally follow the regulation signals, which, however, executes control until the optimum is reached. In [28], online optimization is combined with consensus algorithms to aggregate multiple BESSs in real-time, but the bias uncertainty and energy neutrality are not jointly considered.

Therefore, this paper is concerned with AGC enhancement by exploring the synergy between CGs and an aggregated BESS. Targeting the three challenges mentioned above, an Optimization-based Ramping Reserve Allocation (ORRA) scheme is developed to aggregate and dispatch BESSs that are geographically distributed within a control area. Based on the AIE signals, an online optimization problem is formulated to counteract the AIE by providing ramping capabilities to AGC while minimizing the overall battery usage cost of all nodes. A distributed online optimization algorithm is developed to guarantee the real-time cost-effectiveness and fairness of ORRA, where a dual-bounded technique [28] is integrated to relax the convergence requirements. As a result, the proposed ORRA can significantly enhance AGC performance while avoiding inefficient and counterproductive regulation.

Compared to the previous work, the main contributions and highlights of this paper are summarized as follows:

- We employ black-box modeling [29] for a delicate use of AIE; specifically, online interpolated Radial Basis Functions (RBFs) are arranged into the AIE signals to emulate the aggregated behavior of other FRRs. On these bases, the AGC framework is reformed by taking the AIE as an alternative to the traditional ACE to account for bias uncertainty from both the generation and load sides.
- A aggregation scheme termed ORRA is designed leveraging the AIE, which is essentially zero-mean through the above procedure. Accompanied by the minimization of AIE, our scheme can smoothly discontinue the participation of BESSs by converging their powers back to zero (the appearance of neutrality), taking one step further to energy-neutral operation. In the long run, the accumulated battery exploitation will be negligible.
- Consistent with the geographical distribution of BESSs, the proposed ORRA is fully distributed such that algorithms can be executed in parallel at all nodes. Dynamic regret is used as a performance index for the distributed algorithm versus its centralized counterpart with perfect global information. We show that, under mild conditions, the designed algorithm can provide a sublinear regret guarantee during the real-time implementation.

The rest of this paper is structured as follows. AGC fundamentals, models, and other preliminaries are introduced in Section II. Section III presents the novel scheme termed ORRA, the optimization algorithm, and theoretical results. Comprehensive case studies in Section IV verify the effectiveness of ORRA through simulations on a modified IEEE 14-bus system. Section V concludes this paper.

II. Problem Formulation

A. AGC Framework Considering Bias Uncertainty

An interconnected power system is usually owned by different utilities and partitioned into several control areas. An area has either an import or export of power and is tightly coupled with adjacent areas via tie-lines.

After a disturbance occurs, CGs and the aggregated BESS are obliged to compensate for net-load power mismatch. When the direct acquisition of instantaneous mismatch is unavailable, the ACE is frequently used as a proxy error signal for AGC. The ACE is obtained as the difference between scheduled and actual tie-line power flows $\Delta P_{tie}$ plus a scaled frequency deviation $\Delta f$, that is

$$ACE = \Delta P_{tie} + B\Delta f,$$

where $B$ represents the frequency bias that is adjusted yearly in PJM [20]. As the numerical value of the ACE will be physically meaningful only when $B \leftarrow D + R^{-1}$, the frequency bias should be set as close as possible to the AFRC, which is, however, a joint action of the load damping $D$ and the governor droop response $R^{-1}$.

It should be pointed out that such a linear governor droop response takes place only under ideal assumptions. Under the presence of governor-turbine nonlinearity such as saturation,
ramp-rate limits, and governor dead-bands, CG’s mechanical power deviation in response to a frequency deviation can be described using the following equation. As for the CG at bus \( i \), we have
\[
\Delta P_i^m = \Delta u_i^{gov} - \mathcal{F}_i (\Delta u_i^{gov}, \Delta f),
\]
where \( \mathcal{F}_i : \mathbb{R}^2 \to \mathbb{R} \) and \( \Delta u_i^{gov} \) is the governor input deviation. It indicates that obtaining an explicit analytical solution for \( B \) is difficult.

Integrating (1) and (2) gives the concept of AIE [23], which is able to account for the governor-turbine nonlinearity using feedback of \( \Delta P_i^m \)
\[
AIE = \Delta P_i^{pie} + D' \Delta f + \sum_{i \in G} (\Delta u_i^{gov} - \Delta P_i^m),
\]
where \( D' \) is a tuning parameter associated with \( D \) and \( G \) denotes the set of generator buses. Similarly, we denote \( \mathcal{V} \) as the set of buses, and then the AIE signal assigned to bus \( i \) will be
\[
AIE_i = \sigma_i \left( \Delta P_i^{pie} + D' \Delta f \right) + \Delta u_i^{gov} - \Delta P_i^m,
\]
for \( i \in \mathcal{G} \) and \( AIE_i = 0 \) for \( i \in \mathcal{V} - \mathcal{G} \), where \( \sum_{i \in \mathcal{G}} \sigma_i = 1 \). The resultant AGC performance is subject to the tuning of \( D' \), as reported in [23]. However, subsequent to increasing involvement of FRRs, their contribution is likely to alter the load damping characteristic of existing power systems [30], [31]. A difficulty lies in that the load damping characteristic is highly dynamic, and its value estimated based on the steady-state characteristics might be valid only for the operating condition where it has been derived.

In an attempt to lessen the importance of parameter tuning and get one step closer to full AGC performance, we take into account the aggregated contribution of downstream FRRs, denoted by \( P_{fr}^i \), when generating the AIE signals. As real-time monitoring of \( P_{fr}^i \) incurs extra expenses and cannot be generalized, alternatively, we propose to capture its approximation using online interpolating RBFs [29]. The goal is not to precisely model but rather emulate how these resources behave in response to different levels of frequency deviation based on a limited number of evaluation points.

The following improvements are made to the AIE signals defined by (4) so as to address bias uncertainty from both the generation side and the load side:
\[
\hat{AIE}_i = AIE_i + \sum_{k=1}^{K} \omega_{i,k} \phi_k (|| \Delta f - \Delta f_k ||),
\]
where the second term is the RBF interpolant of \( P_{fr}^i \), \( \omega_{i,k} \) is a weighting factor that needs to be determined, \( K \) is the current number of samples, and \( \phi_k (x) \) is the widely applied Gaussian basis function
\[
\phi_k (x) = \exp (-\xi x^2), \quad \xi \in \mathbb{R}_{>0}.
\]

As illustrated in the bottom of Fig. 1, the interpolation is an iterative process. At the start of a new iteration, the balancing entity for bus \( i \) identifies whether next evaluation of \( P_{fr}^i \) should be conducted. If so, the regulation reserve provided by downstream FRRs will be collected along with the area frequency measurement. The set of these information with \( K \) samples is denoted by \( \mathcal{K}_i = \{ [\Delta f_k, \Delta P_{fr}^i]_k, \forall k \in 1, ..., K \} \). Then, the interpolation matrix, also referred as Gram matrix, is updated according to
\[
[G_i]_{r,c} = \phi_k (|| \Delta f_r - \Delta f_c ||), \quad \forall r, c = 1, ..., K,
\]
and the weighting matrix, denoted by \( \omega_i = [\omega_{i,1}, ..., \omega_{i,K}]^T \), is determined according to
\[
\omega_i = (G_i^T)^{-1} S_i,
\]
where \( S_i = [\Delta P_{fr}^{i,1}, \Delta P_{fr}^{i,2}, ..., \Delta P_{fr}^{i,K}]^T \). There always exists a unique \( \omega_i \) such that the RBF interpolant can reproduce observed behaviors [32]. Note that a distance-based infill method is adopted from our previous work [29] to determine evaluation points for model improvement. The idea is to assure that the next evaluation point is held at a sufficient distance from the previously evaluated points. By doing so, one may assume \( D' \) in (4) to be fixed at 1%-2.5% of the load [23].

B. BESS Model

Consider a battery operation defined over discrete time, where each control interval has a duration of \( \tau \). Regarding the BESS deployed at bus \( i \), its SoC evolution can be described using a linear difference equation:
\[
x_{i,t+1} = x_{i,t} + \frac{\eta_i^+ \tau}{E_i} c_{i,t+1} - \frac{\tau}{\eta_i^- E_i} d_{i,t+1},
\]
where \( x_{i,t+1} \) and \( x_{i,t} \) are respectively the SoC levels of BESS, at time instant \( t \) and \( t + 1 \); \( \eta_i^+ \) and \( \eta_i^- \) are the charging/discharging efficiencies; \( E_i \) is the rated capacity; \( c_{i,t+1} \) and \( d_{i,t+1} \) denote the reference signals for charging and discharging and are treated as equivalent to the instantaneous BESS powers in this formulation, provided that the internal control loops are fast enough.
The BESS can either operate at charging or at discharging mode. Irrespective of the model used, one has to avoid simultaneous charging and discharging. A convenient solution is to invoke a binary variable \( \delta_{i,t} \) that is determined according to
\[
\delta_{i,t} = \begin{cases} 
\frac{1}{2} \frac{AIE_{i,t}}{|AIE_{i,t}|} + 1, & i \in \mathcal{G}, \\
\delta_{i,t} = \delta_{j,t} - \text{dist}(i,j), & i \in \mathcal{V} - \mathcal{G},
\end{cases}
\]
where \( j \in \mathcal{G} \) exhibits the shortest path to \( i \). We then introduce the following constraints:
\[
\begin{align*}
0 & \leq c_{i,t+1} \leq (1 - \delta_{i,t}) \bar{\tau}_i, \\
0 & \leq d_{i,t+1} \leq \delta_{i,t} \bar{\tau}_i,
\end{align*}
\]
such that the BESS is charged if \( \delta_{i,t} = 0 \) and discharged if \( \delta_{i,t} = 1 \), where \( \bar{\tau}_i \) and \( \bar{d}_i \) denote the BESS power limits.

To avoid over-charging and over-discharging, the SoC of each BESS needs to be restricted within an appropriate range:
\[
x_i \leq x_{i,t} + \frac{\eta c_i}{E_i} c_{i,t+1} - \frac{\tau}{\eta d_i} d_{i,t+1} \leq \bar{\tau}_i,
\]
where \( x_i \) and \( \bar{\tau}_i \) are the minimum and maximum SoC levels.

### C. Cost Model

Cycling aging refers to a natural process that leads to permanent battery degradation and is directly determined by the depth for which a battery is cycled. However, the resultant cost of cycling aging is usually omitted [6], [11], [33], [34] or approximated through a simplified model [15], [35], [36]. In contrast, we adopt a semi-empirical model that combines cycle identification results with experimental data [37] to more accurately assess the resultant cost, which, as proven by [27], is strictly convex with respect to charging/discharging powers.

![Fig. 2. Illustration of rainflow-counting algorithm.](image)

Using the well-known rainflow-counting algorithm [38], we are able to identify the cycle depth of the latest half cycle per iteration
\[
(\mu_{i,t}, R_{i,t+1}) = \text{Rainflow}(x_{i,t}, R_{i,t}),
\]
where \( \mu_{i,t} \) is the cycle depth quantifying the relative difference between latest two residues, \( R_{i,t+1} \) is the updated set of residues (the extrema unremoved by rainflow-counting algorithm), and \( x_{i,t} \) is the latest SoC information, which together with \( R_{i,t} \) actually converts SoC trajectories that entail non-uniform fluctuations into consecutive cycles that can be full or half. As illustrated in Fig. 2, a full cycle consists of a charge half cycle and a discharge half cycle, and it might be nested within other cycles when inputting new SoC trajectories.

Subsequently, we characterize the battery lifetime loss with respect to the identified half cycle as
\[
\Delta L_{i,t}(\mu_{i,t}) := \frac{n_{cyc,t}}{2} a \mu_{i,t}^b,
\]
where \( a \) and \( b \) are empirical coefficients [37] that normalize the cycling aging for a full cycle between 0 and 1, while \( n_{cyc,t} \in (0, 1] \) calculates the number of cycles from the time indexes of the latest two residues. Additional quadratic terms on the BESS powers quantify the power wear. As a result, the battery usage cost ($/h), taking account of the power wear and the cycling aging, is given as
\[
f_{i,t}(d_{i,t}, c_{i,t}) := \theta_i^c \cdot (3600/\tau) \cdot \Delta L_{i,t}(\mu_{i,t}) + \theta_i^d \cdot (d_{i,t} - c_{i,t})^2,
\]
where \( \theta_i^c \) and \( \theta_i^d \) are cost coefficients taken from [27], [39]. Note that, by the chain rule, \( \Delta L_{i,t}(\mu_{i,t}) \) is essentially a function of \( d_{i,t} \) and \( c_{i,t} \).

### D. Optimization Problem Formulation

Our framework consists of \( N \) BESSs that are geographically distributed within a control area, where each BESS possesses a local cost function that cannot be revealed to the others. Here we would like to state that (17) is an online optimization problem with time-varying constraints, which requires BESS to first interact with the environment and then observe the remaining AIE. In turn, each BESS will need to raise or lower its output at next time instant, based on the local and neighbors’ observations at time instant \( t \), to meet the instantaneous ramping requirements and thereby counteract the AIE. From this perspective, the optimization problem in terms of cost minimization can be mathematically modeled as follows:

\[
\min_{d_i, c_i} \sum_{i=1}^{N} f_{i,t}(d_i, c_i) \text{ subject to } \quad \sum_{i=1}^{N} (d_i - c_i) = - \sum_{i=1}^{N} AIE_{i,t},
\]
\[
0 \leq c_i \leq (1 - \delta_{i,t}) \bar{\tau}_i, \quad 0 \leq d_i \leq \delta_{i,t} \bar{\tau}_i,
\]
\[
x_i \leq x_{i,t} + \frac{\eta c_i}{E_i} c_{i,t+1} - \frac{\tau}{\eta d_i} d_{i,t+1} \leq \bar{\tau}_i,
\]
where (17a) focuses on the real-time cost-effectiveness of AGC enhancement. \( d_i \) and \( c_i \) are the decision variables being optimized and implemented at time instant \( t + 1 \). The calendar aging independent of charge-discharge cycling is omitted as it is a long-term process beyond the time frame of ORRA.

### III. Proposed Scheme

In this section, we will present the ORRA scheme to solve the problem in (17), which has three distinctive features. First, delicately designed AIE is embedded into the optimization algorithm to quantify the instantaneous ramping requirements to
avoid the effects of miscalculated ACE. Second, the proposed ORRA is able to immediately deploy and smoothly un-deploy BESSs with respect to a frequency event, which contributes to energy-neutral operation. Third, consistent with the geographical distribution of BESSs, the optimization algorithm is fully distributed and can guarantee fair and near-optimal allocation in real-time.

A. Distributed Online Optimization

The interconnected power system is modeled as a multi-agent system. Each BESS is managed by an agent that is responsible for information acquisition/exchange, AIE generation, and algorithm execution and is partially aware of the global cost function and the global constraint due to grid infrastructure and privacy requirements. For the sake of generality, we denote

\[ u_i := [d_i, -c_i]^T, \quad h_{i,t}(u_i) := 1_2^T u_i + A\tilde{H}_{i,t}. \]

(18)

where \( 1_2 = (1, 1) \in \mathbb{R}^2 \).

Replace (17c) with projection operation which projects \( u \) into its decision domain to meet the inequality constraints. Then the Lagrangian function associated with (17) can be reduced to

\[ L_t(u, \lambda) = \sum_{i=1}^{N} f_{i,t}(u_i) + \lambda \sum_{i=1}^{N} h_{i,t}(u_i), \]

(19)

where \( \lambda \) is the dual variable of this problem.

A generalization of algorithm to solve (19) is the Arrow-Hurwicz-Uzawa algorithm that searches for saddle point of convex function, where gradients of primal and dual variables of the Lagrangian function \( L_t \) defined by (19) are used. However, it seems evident from the following formula that the gradients involve global information such as \( \lambda \) and \( \sum_{i=1}^{N} h_{i,t}(u_i) \)

\[ \frac{\partial L_t}{\partial u_i} = \frac{\partial f_{i,t}}{\partial d_i}, \quad \frac{\partial f_{i,t}}{\partial c_i} + 1_2 \lambda, \]

(20)

\[ \frac{\partial L_t}{\partial \lambda} = \sum_{i=1}^{N} h_{i,t}(u_i). \]

(21)

To facilitate a distributed implementation, we consider a peer-to-peer network for agent communication. The communication network can be described by an undirected graph \( G = (V, E) \), where \( V = \{1, \ldots, N\} \) is the set of agents and \( E \subseteq V \times V \) is the set of communication links. Two agents are said to be neighboring if there exists a communication link between them. We introduce a matrix \( W = [w_{ij}] \) to model the communication topology by setting \( w_{ij} \in \mathbb{R}_{>0} \) for \( (i, j) \in E \) and \( w_{ij} = 0 \) otherwise. Note that \( W \) needs to be doubly-stochastic, that is to say, \( \sum_{i=1}^{N} w_{ij} = \sum_{i=1}^{N} w_{ji} = 1 \).

Two auxiliary variables are introduced, and for each agent, the information of itself and its neighbors is weighted sum to compute local estimates of the global information \( \lambda \) and \( \sum_{i=1}^{N} h_{i,t}(u_i) \)

\[ \hat{\lambda}_{i,t} := \sum_{j=1}^{N} w_{ij} \lambda_{j,t}, \quad \hat{y}_{i,t} := \sum_{j=1}^{N} w_{ij} y_{j,t}. \]

(22)

Then, using the local estimate of \( \lambda \), we can rewrite (20) as

\[ s_{i,t} = \left( \frac{\partial f_{i,t}}{\partial d_i} - \frac{\partial f_{i,t}}{\partial c_i} \right) + 1_2 \hat{\lambda}_{i,t}. \]

(23)

Based on (18) and (22)-(23), we develop an optimization algorithm to solve the time-varying problem (17) in a distributed online fashion. The proposed algorithm is summarized in Algorithm 1.

Algorithm 1: Proposed Algorithm for ORRA

Input: parameters \( \alpha, \beta, \gamma, \kappa_0, \epsilon_0 \in \mathbb{R}_{>0} \)

1. Initialization of variables: \( u_{i,0} \in \mathcal{O}_{i,0}, \lambda_{i,0} = 0, \)

\[ y_{i,0} = 1_2^T u_{i,0} + A\tilde{H}_{i,0}; \]

2. Let \( t \leftarrow 0; \)

3. While True do

4. If \( t = 0 \) then

5. Initialize learning rates: \( \kappa_0 \in \mathbb{R}_{>0}, \epsilon_0 \in \mathbb{R}_{>0}; \)

6. Else

7. Update learning rates: \( \kappa_t = \kappa_0 t^{-\alpha}, \epsilon_t = \epsilon_0 t^{-\beta}; \)

8. End

9. For \( i = 1, \ldots, N \) do

10. Obtain local estimates \( \hat{\lambda}_{i,t} \) and \( \hat{y}_{i,t} \) using (22);

11. Obtain gradient search \( s_{i,t} \) using (23);

12. Update \( u_{i,t+1} \) and \( \lambda_{i,t+1} \) based on

\[ u_{i,t+1} = P_{\Omega_{i,t}}(u_{i,t} - \kappa_t s_{i,t}); \]

\[ \lambda_{i,t+1} = (1 - \epsilon_t)\hat{\lambda}_{i,t} + \gamma \kappa_t \hat{y}_{i,t}; \]

(24)

13. Obtain equality constraints on ramping reserve \( h_{i,t}(u_{i,t+1}) \) and \( h_{i,t-1}(u_{i,t}) \) using (18);

14. Update \( y_{i,t+1} \) based on

\[ y_{i,t+1} = \hat{y}_{i,t} + h_{i,t}(u_{i,t+1}) - h_{i,t-1}(u_{i,t}); \]

(26)

15. End

16. Let \( t \leftarrow t + 1; \)

17. If \( t = T \) or \( |\Delta f| \geq 0.05 \) then

18. Reset \( t \leftarrow 0; \)

19. End

20. End

Remark 1. The optimization is an iterative process with an interval of \( \tau \). Adaptive learning rates \( \alpha \) and \( \beta \) are adopted, which start with high learning rates and smoothly decay at certain ratios. If certain conditions are met, i.e., \( t \) reaches the maximum iteration \( T \) or \( \Delta f \) exceeds the limit (0.05 Hz in this paper), the adaptive learning rates will be re-initialized to speed up the optimization and rapidly compensate the AIE at the cost of low accuracy. Their definition domains, together with the regret analysis, can be found in Section III.B. The initial learning rates \( \kappa_0 \) and \( \epsilon_0 \), as well as \( \gamma \in \mathbb{R}_{>0} \) need to be selected for a satisfactory stepsize.

Remark 2. Using Algorithm 1, local information of all nodes, namely \( \lambda_{i,t} \) and \( y_{i,t} \), can be aggregated via the sparse communication network per iteration to steadily enhance ORRA’s perception of global information. At steady-state, we have \( \lambda_t \rightarrow \tilde{\lambda} \) and \( y_t \rightarrow \tilde{y} \) (also, \( \lambda_t \rightarrow \tilde{\lambda} \) and \( y_t \rightarrow \tilde{y} \)), where \( \tilde{\lambda} := 1_N \sum_{i=1}^{N} \lambda_{i,t}/N \) and \( \tilde{y} := 1_N \sum_{i=1}^{N} y_{i,t}/N \). Projection operation \( P_{\Omega_{i,t}} \) in (24) is included to project decision variable \( u_{i,t+1} \) into its decision domain \( \Omega_{i,t} \). A dual-bounded technique...
Lemma 1. For any learning rates $\kappa_t, \epsilon_t \in \mathbb{R}_{>0}$, the following inequality always holds at an arbitrary $T > 1$

\[
\text{Reg}(T) \leq \sum_{t=1}^{T} \frac{1}{2\kappa_t} (\|u_t - u_t^*\|^2 - \|u_{t+1} - u_{t+1}^*\|^2) \\
+ \sum_{t=1}^{T} \frac{1}{2\gamma \epsilon_t} (\|\bar{\lambda}_t\|^2 - \|\bar{\lambda}_{t+1}\|^2) \\
+ \sum_{t=1}^{T} \frac{\kappa_t}{2} \|s_t\|^2 + \sum_{t=1}^{T} \frac{1}{2\gamma \kappa_t} \|s_t - \epsilon_t \bar{\lambda}_t\|^2 \\
+ \sum_{t=1}^{T} \|\bar{\lambda}_t\| \cdot \|\bar{\lambda}_t - \bar{\lambda}_t^*\| + \sum_{t=1}^{T} \|u_t\| \cdot \|\bar{\lambda}_t - \bar{\lambda}_t^*\|. 
\]  

(28)

Proof. The proof of Lemma 1 is provided in Appendix A. \hfill \square

Lemma 2. Let learning rate $\kappa_t \in \mathbb{R}_{>0}$ and $T > 1$. Denote $S(T) := \sum_{t=1}^{T} (\|u_t - u_t^*\|^2 - \|u_{t+1} - u_{t+1}^*\|^2)/(2\kappa_t)$. Denote the bound on decision variables as $B_u$, where $B_u = \max \{\bar{d}_i, \bar{c}_i, \forall i \in 1, ..., N\}$. Then, the following statement is true if and only if $\kappa_t$ decreases progressively with $t$

\[
S(T) \leq 2NB_u^2/\kappa_T + 2NB_uV(T). 
\]  

(29)

Proof. The proof of Lemma 2 is provided in Appendix B. \hfill \square

All these suggest that the boundedness of $\text{Reg}(T)$ relies on a sequence of results and the selection of learning rates. Note that, due to the local inequality constraints, the instantaneous dynamic regret $\sum_{t=1}^{N} f_{t,i}(u_{t,i}) - \sum_{t=1}^{N} f_{t,i}(u_{t,i}^*)$ may not perfectly converge to the exact value of zero at the boundaries of the projected domain. However, the algorithm provides near-optimal operation under most circumstances, and the following assumptions are required to facilitate the derivation of our main results.

Assumption 1. 1) The local cost functions $f_{t,i} : \mathbb{R}^2 \rightarrow \mathbb{R}$ are Lipschitz continuous and there exists a positive constant $C_f$ such that $\|\partial f_{t,i}(x)\| \leq C_f$ for $\forall i \in 1, ..., N$ and $\forall t \in 0, ..., T - 1$.  2) The time-varying disturbances that the interconnected power system is subject to is norm-bounded, which means $\|h_{i,t}\|$ is bounded for $\forall i \in 1, ..., N$ and $\forall t \in 0, ..., T - 1$.

Remark 3. This remark gives some important results for deriving the regret analysis. Under Assumption 1.2, there exists a constant $B_y > 0$ such that $\|u_{t,i}\|$ and $\|s_{t,i}\|$ are both uniformly bounded by $B_y[40]$. When digging into the updating law (25), we have $|\lambda_{i,t+1}| = \|1 - \epsilon_t)\lambda_{i,t} + \gamma \bar{y}_{i,t}| \leq (1 - \epsilon_t)|\lambda_{i,t}| + \gamma B_y$. According to (22) and $\sum_{j=1}^{N}w_{ij} = 1$, one might expect $\|\lambda_{i,t+1}\| = \|\sum_{j=1}^{N}w_{ij}\lambda_{j,t+1}\| \leq \max(|\lambda_{i,t+1}|, \forall i \in 1, ..., N)$. It can be easily verified by mathematical induction that $\|\lambda_{i,t}\|, |\lambda_{i,t}|, |\lambda_{i,t}| \leq \gamma B_y \kappa_t/\epsilon_t$. Further we have $\|s_{i,t}\| \leq \|\partial f_{i,t}(u_{i,t})\| + 1/2 \|\lambda_{i,t}\| \leq C_f + \gamma B_y \kappa_t/\epsilon_t$.

Theorem 1. Let $0 < \alpha \leq \beta < 1$ and $V(T) := \sum_{t=1}^{T} (1/\kappa_t)(u_{t,i}^* - u_{t,i}^*)$. Under Assumption 1 and Algorithm 1, it holds that $\text{Reg}(T) \in \mathcal{O}_{+}(\sum_{t=1}^{T} 2/\kappa_t)$ and $\mathcal{O}_{+}((T^2))$. Furthermore, for the case that $\lim_{T \rightarrow \infty} V(T)T \rightarrow 0$, one can ensure a sublinear dynamic regret with respect to $T$, i.e., $\lim_{T \rightarrow \infty} \text{Reg}(T)/T \rightarrow 0$ if $2\beta - 3\alpha < 0$ and $2\beta - \alpha - 1 > 0$.

Proof. Below, we are in a position to ensure the boundedness of each term of (28) by first identifying their asymptotic growth rates against $T$. Lemma 1 together with Assumption 1 lead to $\lim_{T \rightarrow \infty} S(T)/T = 0$. Now, the second term of (28) can be obtained as

\[
\begin{align*}
\sum_{t=1}^{T} & \frac{1}{2\gamma \kappa_t} (\|\bar{\lambda}_t\|^2 - \|\bar{\lambda}_{t+1}\|^2) \\
& \leq \frac{N}{2\gamma} \left[ \sum_{t=2}^{T} \left( \frac{1}{\kappa_t} - \frac{1}{\kappa_{t-1}} \right) + \frac{1}{\kappa_1} \right] \left( \frac{\gamma B_y \kappa_T}{\epsilon_T} \right)^2 \\
& \leq \frac{N}{2} \left[ \sum_{t=2}^{T} \left( \frac{1}{\kappa_t} - \frac{1}{\kappa_{t-1}} \right) + 1 \right] \left( \frac{\gamma B_y \kappa_T}{\epsilon_T} \right)^2 \\
& \leq \frac{\gamma B_y^2 \kappa_T}{2\epsilon_T^2},
\end{align*}
\]

(30)

By substituting $C_f + 2\gamma B_y \kappa_T/\epsilon_T$ for $\|s_{i,t}\|$ according to Remark 3, the third term of (28) becomes

\[
\sum_{t=1}^{T} \frac{\kappa_t}{2} \|s_t\|^2 \leq \sum_{t=1}^{T} \frac{N}{2} \kappa_t (C_f + 2\gamma B_y \kappa_t/\epsilon_T)^2 \\
= \sum_{t=1}^{T} \frac{N}{2} \left[ C_f^2 t^{-\alpha} + 4\gamma C_f B_y t^{\beta-2\alpha} + 4\gamma B_y^2 t^{2\beta-3\alpha} \right] \left[ \frac{1}{2} \int_1^t t^{1-\beta-2\alpha} dt + 2N\gamma C_f B_y \int_1^t t^{1+\beta-2\alpha} dt \right] \\
+ 2N\gamma B_y^2 \int_t^{t+2\beta-3\alpha} dt + \text{const.}
\]

\[
\in \mathcal{O}_{+}(T^{1+2\beta-3\alpha}).
\]
Similarly, invoking Remark 3 transfers the fourth term of (28) into
\[
\sum_{t=1}^{T} \frac{1}{2\gamma_{\kappa t}} \|\gamma_{\kappa t} \tilde{y}_t - \epsilon_t \tilde{\alpha}_t\|^2
\leq \sum_{t=1}^{T} \frac{1}{2\gamma_{\kappa t}} \left( \gamma^2 B_y^2 \|\kappa_t\|^2 + \|\epsilon_t \tilde{\alpha}_t\|^2 + 2\gamma B_y \|\kappa_t \epsilon_t \tilde{\alpha}_t\| \right)
\leq 2\gamma B_y^2 \sum_{t=1}^{T} \kappa_t
\in \mathcal{O}_{+}(T^{1-\alpha}).
\] (32)

Furthermore, let us apply the results of (28) that \(\sum_{t=1}^{T} \|\tilde{y}_t - \tilde{\tilde{y}}_t\| \in \mathcal{O}_{+}(T^{1+\beta-2\alpha})\) and \(\sum_{t=1}^{T} \|\tilde{\alpha}_t - \tilde{\tilde{\alpha}}_t\| \in \mathcal{O}_{+}(T^{1-\alpha})\).
Hence omitting the less significant terms associated with \(T\) allows us to conclude that
\[
\sum_{t=1}^{T} \|\tilde{\alpha}_t\| \cdot \|\tilde{y}_t - \tilde{\tilde{y}}_t\| + \sum_{t=1}^{T} 2\|u_t\| \cdot \|\tilde{\alpha}_t - \tilde{\tilde{\alpha}}_t\|
\leq \frac{NB_y}{\epsilon_T} \sum_{t=1}^{T} \|\tilde{y}_t - \tilde{\tilde{y}}_t\| + 4NB_u \sum_{t=1}^{T} \|\tilde{\alpha}_t - \tilde{\tilde{\alpha}}_t\|
\leq \frac{NB_y T\kappa T}{\epsilon_T} \cdot \mathcal{O}_{+}(T^{1+\beta-2\alpha}) + 4NB_u \cdot \mathcal{O}_{+}(T^{1-\alpha})
\leq \mathcal{O}_{+}(T^{1+2\beta-3\alpha}).
\] (33)

In the end, summarizing (28)-(33) completes the proof. \(\square\)

IV. SIMULATION STUDY

A modified IEEE-14 bus system is constructed based on MATLAB/Simulink environment, where two control areas (separated by the dotted line) and six CGs with a total generation of 50 MW are specified, as shown in Fig. 3. It is supposed that the generation of RES is subject to variability and uncertainty and is treated as load fluctuations. It is worth remarking that we single out area 1 as the research object and consider BESS participation. Five BESSs are aggregated for use in Area 1 and each of them is allocated an agent. According to Theorem 1, we select \(\alpha = 1/2\) and \(\beta = 3/4\), while a control interval of 0.1s is considered. The communication network is illustrated in Fig 4, which can be mathematically described using a 5x5 matrix that is explained in Section III.A. Note that each line represents a two-way communication link between networked agents and the topology is rather flexible but should contain at least a path between any two agents. For each BESS, the capacity is 2 MWh, the peak power is 1 MW, the efficiencies for charging and discharging are both 0.95, and the initial SoC is arbitrarily chosen from [0.2, 0.8].

A. Case Study 1

This case study is provided as a calibration to examine the effectiveness and features of ORRA with respect to a step change. A load increase of 5 MW is introduced to Area 1 at \(t = 10s\), and the simulation results are given in Fig. 5 and Fig. 6. As it can be observed from Fig. 5(a), all BESSs contribute differently to AGC, owing to their intrinsic heterogeneities, and gradually detach from AGC by resettling their powers to zero. In Fig. 5(b), their marginal costs are maintained almost identical all the time, implying the fairness of allocation during the entire event.

In Fig. 5(c), the instantaneous cost of all nodes of the proposed scheme is also compared with its centralized counterpart (MATLAB “fmincon” optimizer, a solver for constrained nonlinear convex optimization) having full access to global information, where the blue curve represents \(\sum_{i=1}^{N} \sum_{t=1}^{T} f_{i,t}(u_{i,t})\), the results of ORRA, and the red curve represents \(\sum_{i=1}^{N} \sum_{t=1}^{T} f_{i,t}(u^*_{i,t})\), the results of “fmincon” from a centralized view. It can be seen that only slight inconsistency between \(\sum_{i=1}^{N} \sum_{t=1}^{T} f_{i,t}(u_{i,t})\) and \(\sum_{i=1}^{N} \sum_{t=1}^{T} f_{i,t}(u^*_{i,t})\) is observed (mainly caused by the equality constraint not fully met) and our distributed scheme achieves the near-optimal allocation comparable to the centralized scheme, which is in line with the regret analysis in Section III.B.

Then, the proposed scheme are compared with three control groups and the results are given in Fig. 6. To avoid confusion, we outline that

- AIE+BESS: AIE-based AGC with BESS participation (i.e., the proposed scheme termed ORRA);
- ACE+BESS: ACE-based AGC with BESS participation;
- AIE: AIE-based AGC without BESS participation;
Fig. 5. Optimization results regarding a 5 MW net-load change in Area 1.

- ACE: ACE-based AGC without BESS participation.

Compared to the black lines marked with “ACE” and “AIE”, the magnitudes of frequency drops are greatly reduced in the presence of aggregated BESS due to the capabilities of responding fast and precisely they offered. It is worth noticing that the BESSs may fall into an inefficient regulation, as highlighted in Fig. 6 with red block, due to the miscalculation of ACE in the presence of bias uncertainty. As discussed in Section II.A, the ACE implicitly assumes a linear turbine-governor response and time-invariant load damping characteristic. On the contrary, the AIE permits a dynamic frequency bias to track with the AFRC and hence mitigates the impact of bias uncertainty, which is vital for BESS aggregation. Consequently, the corresponding response displays a significant enhancement in AGC performance, which is quantified by comparing the responses of “AIE+BESS” and “AIE” and also highlighted in Fig. 6 with blue block.

B. Case Study 2

Seeing that ORRA was examined only under discharging mode, case study 2 is designed by extending the time span of case study 1 and introducing net-load fluctuations to further assess the effectiveness of ORRA. With positive values representing power deficiency and power surplus vice versa, the net-load fluctuations are generated as uniformly distributed random numbers ranging from -6 MW to 6 MW, as represented by the yellow dotted line in Fig 7(a). As a consequence, the BESSs have to frequently shift between discharging mode and charging mode to counteract the AIE. The blue line represents the total power of four CGs and the red line represents the power of aggregated BESS. Instructed by the AIE signals, the aggregated BESS acts in collaboration with the CGs to correct the mismatch, showing a complementarity between two classes of regulation resources. This complementary advantage is more evident when CGs’ ramping capabilities are inadequate to meet the regulation requirements. For instance, in response to the mismatch at \( t = 800 \) s, the CGs take about 100 s to ramp up to 2.7 MW and there clearly will be a gap in the provision of AGC without aggregated BESS. Furthermore, the frequency response under ORRA is compared with a benchmark system [11] to illustrate the advantages of ORRA, and the results are given in Fig. 7(b). Fig. 7(c) illustrates the SoC levels over the entire time span. In the long run, the aggregated BESS at a relatively low instantaneous power can significantly enhance AGC performance, and their operation is virtually energy-neutral as the SoC levels are closely kept around their initial values.

V. CONCLUSION

In this paper, three crucial challenges hindering the regulation efficiency of aggregated BESS in AGC have been addressed. First, we have employed black-box modeling for a delicate use of AIE to account for various bias uncertainty from both the generation and load sides. Second, for the sake of energy-neutral operation, we have developed a aggregation scheme based on those AIE signals, called ORRA, which can smoothly terminate the participation of BESSs by recovering their powers to zero. Third, an optimization algorithm has been developed to solve the formulated online optimization problem in a distributed fashion, which has been proven to have a sublinear dynamic regret under properly designed learning rates. Simulation studies have been carried out to demonstrate
the effectiveness of ORRA both in AGC enhancement and resource allocation.

VI. APPENDIX

A. Proof of Lemma 1

Proof. According to (19) and \( \sum_{t=1}^{T} h_{t,t}(u_{t}^*) = 0 \), we have that \( \text{Reg}(T) \equiv \sum_{t=1}^{T} L_t(u_t, \mathbf{0}_N) - \sum_{t=1}^{T} L_t(u_t^*, \bar{\lambda}_t) \), which allows us to rewrite the dynamic regret as

\[
\text{Reg}(T) = \sum_{t=1}^{T} \left[ L_t(u_t, \mathbf{0}_N) - L_t(u_t^*, \bar{\lambda}_t) \right] + \sum_{t=1}^{T} \left[ L_t(u_t, \bar{\lambda}_t) - L_t(u_t^*, \bar{\lambda}_t) \right].
\] (34)

To move forward, we need to obtain the upper bounds of \( \sum_{t=1}^{T} \left[ L_t(u_t, \mathbf{0}_N) - L_t(u_t^*, \bar{\lambda}_t) \right] \) and \( \sum_{t=1}^{T} \left[ L_t(u_t, \bar{\lambda}_t) - L_t(u_t^*, \bar{\lambda}_t) \right] \). From updating law (25), we have

\[
\| \bar{\lambda}_{t+1} - \bar{\lambda}_t \|^2 = \| \bar{\lambda}_t + (\gamma \kappa_t \bar{y}_t - \epsilon_t \bar{\lambda}_t) \|^2 \geq \| \bar{\lambda}_t \|^2 + 2 \gamma \kappa_t \bar{y}_t - \epsilon_t \bar{\lambda}_t \|^2 + 2 \gamma \kappa_t \bar{y}_t - \epsilon_t \bar{\lambda}_t \|^2 + 2 \gamma \kappa_t \bar{y}_t - \epsilon_t \bar{\lambda}_t \|^2.
\] (35)

Since \( \bar{y}_t \bar{\lambda}_t = (\bar{y}_t - \bar{y}_t^T \bar{\lambda}_t + \bar{y}_t - \bar{y}_t^T \bar{\lambda}_t \), \( \bar{y}_t \bar{\lambda}_t = L_t(u_t, \bar{\lambda}_t) - L_t(u_t, \mathbf{0}_N) \), (35) gives the result that the first term of (34) satisfies

\[
L_t(u_t, \mathbf{0}_N) - L_t(u_t, \bar{\lambda}_t) \\
\leq \frac{1}{2 \gamma \kappa_t} (\| \bar{\lambda}_t \|^2 - \| \bar{\lambda}_{t+1} \|^2) + \frac{1}{2 \gamma \kappa_t} \| \gamma \kappa_t \bar{y}_t - \epsilon_t \bar{\lambda}_t \|^2 \] (36)

As the next step, recalling updating law (24), along the property possessed by projection mapping that \( \| P_t(x) - P_t(y) \| \leq \| x - y \| \) yields

\[
\| u_{t+1} - u_t^* \|^2 \leq \| u_t - u_t^* - \kappa_t \bar{s}_t \|^2 \\
\leq \| u_t - u_t^* \|^2 + \| \kappa_t \bar{s}_t \|^2 - 2 \kappa_t \bar{s}_t^T (u_t - u_t^*). \] (37)

By the first-order property of characterization of convex functions, we have \( -2 \kappa_t \bar{s}_t^T (u_t - u_t^*) \leq -2 \kappa_t \left[ f_t(u_t) - f_t(u_t^*) \right] \). As a result of \( f_t(u_t) - f_t(u_t^*) = L_t(u_t, \bar{\lambda}_t) - L_t(u_t^*, \bar{\lambda}_t) \), we can further conclude that

\[
L_t(u_t, \bar{\lambda}_t) - L_t(u_t^*, \bar{\lambda}_t) \\
\leq \frac{1}{2 \kappa_t} (\| u_t - u_t^* \|^2 - \| u_{t+1} - u_{t+1}^* \|^2) + \frac{\kappa_t}{2} \| \bar{s}_t \|^2 \] (38)

Substituting (36) and (38) into (34) and rearranging the terms ends the proof. \( \square \)

B. Proof of Lemma 2

Proof. We regroup \( S(T) \) as the summation of \( S_1(T) \) and \( S_2(T) \) for notational simplicity, as shown by

\[
S(T) = \sum_{t=1}^{T} \frac{1}{2 \kappa_t} (\| u_t - u_t^* \|^2 - \| u_{t+1} - u_{t+1}^* \|^2) \\
+ \sum_{t=1}^{T} \frac{1}{2 \kappa_t} (\| u_{t+1} - u_{t+1}^* \|^2 - \| u_{t+1} - u_{t+1}^* \|^2) . \] (39)
By taking the similar approach alike (30), $S_1(T)$ can be rearranged as

$$S_1(T) = \frac{1}{2k_1} \|u_1 - u_1^*\|^2 - \frac{1}{2k_{T+1}} \|u_{T+1} - u_{T+1}^*\|^2 + \frac{1}{2} \sum_{t=1}^{T} \left( \frac{1}{\kappa_t} - \frac{1}{\kappa_{t-1}} \right) \|u_t - u_t^*\|^2$$

$$\leq 2NB^2 u_n / \kappa T.$$  \hfill (40)

From $\|x\|^2 - \|y\|^2 \leq \langle x + y, x - y \rangle$, it can be easily seen that

$$S_2(T) \leq \sum_{t=1}^{T} \frac{1}{2k_t} \left( \|u_{t+1}\|^2 + \|u_{t+1}^*\|^2 + \|u_t^*\|^2 \right) \cdot \|u_t^* - u_{t+1}\|^2 \leq 2NBu(V).$$

Combining the results of (40) and (41) completes the proof.  \hfill \Box

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