Optimization-Based Ramping Reserve Allocation in AGC Avoiding Counterproductive Regulation

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Abstract—It has been observed in practice that Battery Energy Storage Systems (BESSs) may not always contribute to the minimization of Area Control Error (ACE). This phenomenon of “counterproductive regulation” is open to a number of interpretations. For one thing, cost-effective coordination of distributed BESSs has not been well-established and requires much more research efforts. For another, the 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 in order to recover an energy-neutral state. Leveraging corrected ACE signals, this paper explores a novel scheme termed Optimization-based Ramping Reserve Allocation (ORRA) to coordinate a group of BESSs in Automatic Generation Control (AGC). The underlying methodology is to counteract net-load forecasting errors by providing only ramping reserves rather than capacity reserves to AGC, based on which an online optimization problem is formulated to minimize the associated battery usage cost of all nodes. The corresponding optimization algorithm is purely distributed and can guarantee fair and near-optimal allocation in real-time while avoiding those counterproductive behaviors mentioned above. Simulations on a modified IEEE 14-bus system are performed to illustrate the effectiveness of ORRA in both allocation and AGC enhancement.

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 RES [1], [2]. Recognizing the operational challenges, policymakers and Independent System Operators (ISOs) around the world, such as PJM, ISO New England (ISO-NE), and Capacity Market (CM), have actively engaged in the commercial use of Battery Energy Storage Systems (BESSs) in the provision of grid services to hedge against the variability and uncertainty associated with RESs.

Automatic Generation Control (AGC) is a balancing mechanism at the secondary control level for maintaining active power balance in the real-time dispatch, which has an 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, which means that the ACE will inevitably be amplified. Second, because of its fast-ramping capability, the BESS can reach its dispatch target faster and then be re-dispatched more often.

However, it has been observed in some electricity markets that the BESSs may not always contribute to the minimization of ACE as expected but give rise to counterproductive regulation [7]. This phenomenon is the result of joint action between three possible factors, which primarily motivates the Optimization-based Ramping Reserve Allocation (ORRA) proposed in this paper:

1) Uncoordinated Regulation: Achieving the full potential of BESS to benefit AGC is still an open challenge. This is due to the lack of explicit instructions on how much each should contribute to AGC, as well as the self-interest nature of service providers [7]. Traditional AGC systems [8], as a trade-off, consider a powerful central controller to aggregate the availability of all resources and give a proportional/priority-based allocation, which apparently cannot guarantee the cost-effectiveness of AGC. On this point, a variety of optimization-based strategies have been proposed in recent research, based on Model Predictive Control (MPC) [9], [10], Approximate Dynamic Programming (ADP) [11], and Deep Reinforcement Learning (DRL) [12], [13]. DRL is trained offline with massive collected data and then deployed online (quite often, DRL has low sampling efficiency and quite poor adaptiveness to changing environments, e.g., weather). ADP and MPC can be implemented online but may require extensive computational power, especially when their prediction horizon is large. In contrast, online optimization [14], [15] shows promise for real-time implementation since it is computationally more efficient [16]. In [14], an online optimization policy is tailored for BESS to follow the regulation signals, where policy iteration is adopted to solve the formulated optimization problem. In [15], online optimization is combined with consensus algorithms to cost-effectively coordinate multiple BESSs to restore system frequency.

2) Energy Neutrality: This is a concept requesting the cumulative energy input of a BESS to equal its cumulative energy output. In this context, some BESSs may have to move in opposition to what we expect for regulation in order to recover an energy-neutral state [17], or need to include a comprehensive State-of-Charge (SoC) control such that the BESS acts only during designated periods [3], both of which imply a low regulation efficiency. Without converging BESS powers eventually to zero (the appearance of neutrality), continuous charge or discharge will lead to SoC drifts and not allow for sustainability. Despite its significant and widely perceived importance in BESSs control, energy neutrality was not taken...
as seriously as it should have been, sometimes deliberately overlooked in many studies [9]–[11], [13], [15]. Regarding energy neutrality, PJM and ISO-NE split the ACE, batch-by-batch, into an AGC setpoint for CGs every few seconds and a fast, continuous signal that is meant to be energy-neutral for BESSs [18]. Such an energy-neutral signal keeps the BESS from being over-charged or over-discharged, which is critical to its operating integrity. Modifications to the regulation allocation process and AGC frameworks are also feasible options. In California ISO (CAISO) and Midcontinent ISO (MISO), fast-ramping resources are prioritized in AGC and rewarded for providing ramping-up/down services according to a mileage payment, without substituting for spinning reserves offered by CGs [19]. Compared to the signal design, this kind of approach without filtering can better exploit the ramping capabilities of BESSs.

3) Bias Uncertainty: BESS could be misled by miscalculated ACE and, in turn, result in subsequent counterproductive behavior. 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 and the load damping. 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. Even a static bias uncertainty at 5% can have non-negligible impacts on settling time and cause unintended interaction between control areas [21]. As a result, targeted processing of various bias uncertainties is necessary, especially for future power systems where the load damping can vary substantially within a single day. Recently, the concept of Area Injection Error (AIE) has been proposed in [22], which corrects the ACE by removing the bias uncertainty manifested as nonlinear turbine-governor responses; still, the bias uncertainty from the load side remains unresolved since there is a parameter with respect to the load damping to be elaborately tuned.

In addition to the energy neutrality needs and bias uncertainty, [11], [13], [14] apply only to a single BESS, and the centralized schemes in [9], [10], [12] deviate from the intrinsic heterogeneity and distributed deployment of BESSs and can be inefficient in terms of communication infrastructure. As a result, this paper is concerned with two issues that need further investigation: 1) how to better coordinate distributed BESSs to complement CGs for AGC enhancement 2) how to account for the potential “counterproductive regulation” during BESS participation.

To begin with, this paper takes the AIE as an alternative to the traditional ACE for the design of AGC frameworks. It is worth remarking that, under delicate operation and control design, the AIE is essential zero-mean from a long-term view and only in that case can be directly adopted as the expected ramping requirements without being filtered first for an energy-neutral operation. In this regard, we employ black-box modeling [23] to reduce the importance of parameter tuning 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 Frequency Response Reserves (FRRs) that can result in bias uncertainty on the load side. On these bases, an online optimization problem regarding ORRA of a group of BESSs is formulated to counteract the AIE by providing only ramping capabilities to AGC, which aims to minimize 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 [24] is integrated to relax our convergence requirements. The rationale behind this is to iteratively solve the online optimization problem by first interacting with the environment and then utilizing local and neighbors’ observations for decision-making. The algorithm is fully distributed so that the computational tasks are executed in parallel over all nodes by virtue of neighborhood communication, and it has been rigorously proven to be able to achieve a sublinear convergence rate of dynamic regret under mild conditions. The effectiveness of ORRA is validated through simulations on a modified IEEE 14-bus system.

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

- Regarding the first issue, a novel scheme termed ORRA is proposed via online optimization to coordinate a group of BESSs in AGC. The optimization algorithm, which is fully distributed, can achieve near-optimal and fair allocation of ramping reserves in real-time. Very few studies have been conducted in this direction.
- Regarding the second issue, the concept of AIE is combined with properly designed ORRA to account for the bias uncertainty and energy neutrality to further avoid counterproductive regulation. Those important features were barely considered in existing works.
- By counteracting the AIE and complementing CGs, the BESS participation can significantly improve AGC performance. Besides, the BESS powers converge to zero at steady-state, and hence, in the long run, the accumulated battery exploitation is negligible.

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. Section V concludes this paper.

II. Problem Formulation

A. AGC Framework Considering Bias Uncertainties

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, balancing entities are obliged to compensate for instantaneous changes in generation and load. 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 $B < D + R^{-1}$, 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. Due to governor-turbine nonlinearity such as saturation, ramp-rate limits, and governor dead-bands, CG’s mechanical power deviation in response to a frequency deviation is actually a nonlinear function. For the CG at bus $i$, we have

$$\Delta P_{im}^i = \Delta u_{i}^{gov} - \mathcal{F}_i \left( \Delta u_{i}^{gov}, \Delta f \right),$$

where $\mathcal{F}_i : \mathbb{R}^2 \rightarrow \mathbb{R}$ and $\Delta u_{i}^{gov}$ 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 [22], which successfully accounts for the governor-turbine nonlinearity using feedback of $\Delta P_{im}$,

$$AIE_i = \Delta P_{tie} + D' \Delta f + \sum_{i \in \mathcal{G}} \left( \Delta u_{i}^{gov} - \Delta P_{im}^i \right),$$

where $D'$ is a tuning parameter associated with $D$ and $\mathcal{G}$ denotes the set of generator buses. Similarly, we denote $\mathcal{V}$ as the set of buses and $\mathcal{V} - \mathcal{G}$ the set of rest buses. In this context, the AIE signal assigned to bus $i$ will be

$$AIE_i = \sigma_i \left( \Delta P_{tie} + D' \Delta f \right) + \Delta u_{i}^{gov} - \Delta P_{im}^i,$$

for $i \in \mathcal{G}$ and $AIE_i = 0$ for $i \in \mathcal{V} - \mathcal{G}$, where $\sigma_i$ is a weighting factor for the CG at bus $i$. The resulting AGC performance is subject to the tuning of $D'$, as reported in [22]. Subsequent to increasing involvement of FRRs, their contribution is likely to alter the load damping of existing power systems [25], [26]. However, a difficulty of the tuning lies in that the load damping 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 aggregate 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 iteratively interpolating RBFs. 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 the bias uncertainties from both the generation side and the load side:

$$\hat{AIE}_i = AIE_i + \sum_{k=1}^{K} \omega_{i,k} \phi_i \left( \| \Delta f - \Delta f_k \| \right),$$

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 $\phi_i(x)$ is the widely applied Gaussian basis function

$$\phi_i(x) = \exp(-\xi x^2), \quad \xi \in \mathbb{R}_{>0}.$$  

As illustrated in 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 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 $K_i = \{ \Delta f_k, \Delta P_{fr}^k \|, \forall k \in 1, ..., K \}$. Then, the Gram matrix is updated according to

$$(G_i)_{rc} = \phi_i \left( \| \Delta f^r - \Delta f_c^c \| \right), \quad \forall r,c = 1, ..., K,$$

and the weighting matrix, denoted by $\omega_i = [\omega_{i,1}, ..., \omega_{i,K}]^\top$, is determined according to

$$\omega_i = (G_i^\top)^{-1} S_i,$$

where $S_i = [\Delta P_{fr}^{i,1}, \Delta P_{fr}^{i,2}, ..., \Delta P_{fr}^{i,K}]^\top$. There always exists a unique $\omega_i$ such that the RBF interpolant can reproduce observed behaviors. Note that a distance-based infill method is adopted from our previous work [23] 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 [22].

**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:

$$x_{i,t+1} = x_{i,t} + \gamma_i \frac{\tau}{E_i} c_{i,t+1} - \frac{\tau}{\eta_i E_i} d_{i,t+1},$$

(9)

where $x_{i,t+1}$ and $x_{i,t}$ are respectively the SoC levels of BESS at time instant $t$ and $t + 1$; $\gamma_i$ 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 $\delta_{i,t}$ such that the BESS is charged if $\delta_{i,t} = 0$ and discharged if $\delta_{i,t} = 1$. In this paper, $\delta_{i,t}$ is obtained according to

$$\delta_{i,t} = \begin{cases} \frac{1}{2} \left( \frac{AIE_{i,t}}{AIE_{i,t}} + 1 \right), & i \in \mathcal{G}, \\ \delta_{j,t} - \text{dist}(i,j), & i \in \mathcal{V} - \mathcal{G}, \end{cases}$$

(10a)

$$\delta_{i,t} = \delta_{j,t} - \text{dist}(i,j), & i \in \mathcal{V} - \mathcal{G},$$

(10b)

where $j \in \mathcal{G}$ exhibits the shortest path to $i$. To illustrate, we take the communication topology in Fig. 4 as an example, from which we have $\delta_{i,t} = \delta_{k,t-1} - \delta_{k,t-1}$. We thus have the following constraints:

$$0 \leq c_{i,t+1} \leq (1 - \delta_{i,t}) \overline{c}_i,$$

(11)

$$0 \leq d_{i,t+1} \leq \delta_{i,t} \overline{d}_i,$$

(12)

where $\overline{c}_i$ and $\overline{d}_i$ 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:

$$x_1 \leq x_{i,t} + \frac{\eta_i \tau}{E_i} c_{i,t+1} - \frac{\tau}{\eta_i E_i} d_{i,t+1} \leq x_2,$$

(13)

where $x_1$ and $x_2$ 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 or approximated through a simplified model or practiced experimentally. In contrast, we adopt a semi-empirical model that combines cycling identification results with experimental data to more accurately assess the resultant cost, which, as proven by [14], is strictly convex with respect to charging/discharging powers.

Using the well-known rainflow-counting algorithm, we are able to identify the cycle depth of the latest half cycle almost concurrently with the rest procedure per iteration

$$(\mu_{i,t}, R_{i,t+1}) = \text{Rainflow}(x_{i,t}, \mathcal{R}_{i,t}),$$

(14)

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, 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

$$\Delta L_{i,t}(\mu_{i,t}) := \frac{n_{i,t} \mu_{i,t}}{2 \mu_{i,t}^b},$$

(15)

where $a$ and $b$ are empirical coefficients that normalize the cycling aging for a full cycle between 0 and 1, while $n_{i,t} \in [0, 1]$ 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 ($$/h$$), accounting the power wear and the cycling aging, is given as

$$f_{i,t}(d_{i,t}, c_{i,t}) := \theta_i^c \cdot (3600 / \tau \cdot \Delta L_{i,t}(\mu_{i,t})) + \theta_i^p \cdot (d_{i,t} - c_{i,t})^2,$$

(16)

where $\theta_i^c$ and $\theta_i^p$ are cost coefficients taken from [14], [33]. 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 a group of $N$ BESSs geographically distributed over a control area, where each of them possesses a local cost function that cannot be revealed to the others. In response to the AIE signals received, each BESS will need to raise or lower its output to instantly meet the requirements of others. In this context, the optimization problem can be mathematically modeled as follows:

$$\min \sum_{i=1}^{N} f_{i,t}(d_{i,t}, c_{i,t})$$

subject to

$$\sum_{i=1}^{N} (d_{i,t} - c_{i,t}) = - \sum_{i=1}^{N} AIE_{i,t},$$

(17a)

$$0 \leq c_{i,t+1} \leq (1 - \delta_{i,t}) \overline{c}_i,$$

(17b)

$$0 \leq d_{i,t+1} \leq \delta_{i,t} \overline{d}_i,$$

(17c)

$$\overline{c}_i \leq x_{i,t} + \frac{\eta_i \tau}{E_i} c_{i,t+1} - \frac{\tau}{\eta_i E_i} d_{i,t+1} \leq \overline{d}_i.$$
then observe the remaining AIE. Moreover, the calendar aging independent of charge-discharge cycling is omitted from [17] as it is a long-term process beyond the time frame of ORRA.

III. PROPOSED SCHEME

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

\[ u_i := [d_i, -c_i]^T, \quad h_{i,t}(u_i) := 1^T u_i + AT E_{i,t}. \]  

(18)

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

Replace the inequality constraints in (17) using projection operation. 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. such that \(\sum_{i=1}^{N} L_{i,t}(u_i, \lambda) = L_t(u, \lambda)\). The gradients with respect to the primal and dual variables can be easily obtained as

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

(20)

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

(21)

It seems evident that both \(\lambda\) and \(\sum_{i=1}^{N} h_{i,t}(u_i)\) involve global information that is unavailable under distributed implementation. Thus, the well-known primal-dual algorithms for finding the globally optimal solution to (19) cannot be directly applied.

A. Distributed Online Optimization

To facilitate the distributed implementation, we consider a peer-to-peer network for agent communication. The communication network can be described as an undirected graph \(G = (\mathcal{V}, \mathcal{E})\), where \(\mathcal{V} = \{1, \ldots, N\}\) is the set of agents and \(\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}\) 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 \((i, j) \in \mathcal{E}\) and \(w_{ij} = 0\) otherwise. Note that \(W\) needs to be doubly-stochastic, that is to say, \(\sum_{j=1}^{N} w_{ij} = \sum_{i=1}^{N} w_{ji} = 1\).

Now we are ready to construct intermediate variables for the global information mentioned earlier

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

(22)

where \(\tilde{\lambda}_{i,t}\) is a local estimate of the dual variable and \(\tilde{y}_{i,t}\) is a local estimate of the ramping requirements. By doing so, each agent is enabled to enhance its perception of global information per iteration. Then we can rewrite (20) as

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

(23)

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

Algorithm 1: Proposed Algorithm for ORRA

\begin{algorithm}
\caption{Proposed Algorithm for ORRA}
\begin{algorithmic}[1]
\STATE \textbf{Input:} parameters \(\alpha, \beta, \gamma, \kappa_0, \epsilon_0 \in \mathbb{R}_{>0}\)
\STATE \textbf{Initialization of variables:} \(u_{i,0} \in \Omega_{i,0}, \lambda_{i,0} = 0, y_{i,0} = 1_N^T u_{i,0} + AT E_{i,t}(0)\);
\WHILE {\(t < T\)}
\IF {\(t = 0\)}
\STATE \textbf{Initialize learning rates:} \(\kappa_0 \in \mathbb{R}_{>0}, \epsilon_0 \in \mathbb{R}_{>0};\)
\ELSE
\STATE \textbf{Update learning rates:} \(\kappa_t = \kappa_0 t^{-\alpha}, \epsilon_t = \epsilon_0 t^{-\beta};\)
\ENDIF
\FOR {\(i = 1, \ldots, N\)}
\STATE \textbf{Obtain local estimates} \(\tilde{\lambda}_{i,t}\) and \(\tilde{y}_{i,t}\) using (22);\n\STATE \textbf{Obtain gradient search} \(s_{i,t}\) using (23);\n\STATE \textbf{Update} \(u_{i,t+1}\) and \(\lambda_{i,t+1}\) based on
\[ u_{i,t+1} = P_{\Omega_{i,t}}(u_{i,t} - \kappa_t s_{i,t}); \]  
\[ \lambda_{i,t+1} = (1 - \epsilon_t)\tilde{\lambda}_{i,t} + \gamma \kappa_t \tilde{y}_{i,t}; \]  
\STATE \textbf{Obtain equality constraints on ramping reserve} \(h_{i,t}(u_{i,t+1})\) and \(h_{i,t-1}(u_{i,t})\) using (18);\n\STATE \textbf{Update} \(y_{i,t+1}\) based on
\[ y_{i,t+1} = \tilde{y}_{i,t} + h_{i,t}(u_{i,t+1}) - h_{i,t-1}(u_{i,t}); \]  
\ENDFOR
\STATE \textbf{let} \(t \leftarrow t + 1\);
\IF {\(t = T\) or \(|\Delta f| \geq 0.05\)}
\STATE \textbf{reset} \(t \leftarrow 0;\)
\ENDIF
\ENDWHILE
\end{algorithmic}
\end{algorithm}

Remark 1. The optimization is an iterative process with a maximum iteration of \(T\), and it will be re-initialized when certain conditions are met by setting \(t\) to 0. Adaptive learning rates \(\alpha\) and \(\beta\) are adopted to speed up the optimization process by starting with high learning rates and gradually lowering them until the minimum is reached. Their definition domains, together with the regret analysis, can be found in Section III.B. \(\gamma \in \mathbb{R}_{>0}\) should be tuned based on which the priority is, i.e., strictly adhering to the formulated optimization problem or providing fast-ramping capabilities. The initial learning rates \(\kappa_0\) and \(\epsilon_0\) need to be selected for a satisfactory stepsize.

Remark 2. Two variables, namely \(\tilde{\lambda}_{i,t}\) and \(\tilde{y}_{i,t}\), are shared for use such that the global information can be steadily aggregated via the communication network. At steady-state, we have \(\lambda_t \rightarrow \tilde{\lambda}_t\) and \(y_t \rightarrow \tilde{y}_t\), where \(\tilde{\lambda}_t := 1_N^T \lambda_t/N\) and \(\tilde{y}_t := 1_N^T y_t/N\). 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 [24] is integrated in (25) to impede the growth of \(\lambda_{i,t}\) using \(\epsilon_t\) and relax our convergence requirements. As CGs slightly ramp up/down and minimize the AIE, the BESSs gradually withdraw their
contribution to AGC after instantly ramping up. This will ultimately lead to \( d_T = 0_N \) and \( c_T = 0_N \) if there are no further disturbances, which is of particular importance in avoiding SoC drifts and de-emphasizing SoC control \cite{4, 17}.

### B. Regret Analysis

Due to the time-varying nature of online optimization, dynamic regret is introduced to define its convergence. This performance metric is computed for each iteration and summed up to measure how much the battery actions deviate from the best trajectory from an offline view. The dynamic regret at arbitrary \( T > 1 \) is defined as

\[
Reg(T) = \sum_{t=1}^{T} \sum_{i=1}^{N} f_{i,t}(u_{i,t}) - \sum_{t=1}^{T} \sum_{i=1}^{N} f_{i,t}(u_{i,t}^*) \tag{27}
\]

**Lemma 1.** For any learning rates \( \kappa_i, \epsilon_i \in \mathbb{R}_{>0} \), the following inequality always holds at arbitrary \( T > 1 \)

\[
Reg(T) \leq \sum_{t=1}^{T} \frac{1}{2\kappa_i} \left( \|u_t - u_t^*\|^2 - \|u_{t+1} - u_t^*\|^2 \right) + \sum_{t=1}^{T} \frac{1}{2\gamma\kappa_i} \left( \|\tilde{\lambda}_t\|^2 - \|\tilde{\lambda}_{t+1}\|^2 \right) + \sum_{t=1}^{T} \frac{\kappa_i}{2\gamma} \|s_t\|^2 + \sum_{t=1}^{T} \frac{1}{2\gamma\kappa_i} \|\gamma\kappa_i \tilde{y}_t - \epsilon_t \tilde{\lambda}_t\|^2 + \sum_{t=1}^{T} \|\tilde{\lambda}_t\| \cdot \|\tilde{y}_t - \tilde{y}_t\| + \sum_{t=1}^{T} 2\|u_t\| \cdot \|\tilde{\lambda}_t - \tilde{\lambda}_t\| \tag{28}
\]

**Proof.** The proof of Lemma 1 is provided in Appendix A. \( \square \)

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

\[
S(T) \leq 2NB_u^2/\kappa_T + 2NB_aV(T) \tag{29}
\]

**Proof.** The proof of Lemma 2 is provided in Appendix B. \( \square \)

All these suggest that the boundedness of \( Reg(T) \) relies on a sequence of results and the selection of learning rates. Note that, due to the local inequality constraints, the instantaneous dynamic regret \( \sum_{t=1}^{N} f_{i,t}(u_{i,t}) - \sum_{t=1}^{N} f_{i,t}(u_{i,t}^*) \) 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 graph \( G \) is strongly connected and the weighting matrix \( W \) is doubly-stochastic.

2) The local cost functions \( f_{i,t} : \mathbb{R}^2 \to \mathbb{R} \) are Lipschitz continuous and there exists a positive constant \( C_f \) such that \( \|\partial f_{i,t}(x)\| \leq C_f \) for \( \forall i \in 1, ..., N \) and \( \forall t \in 0, ..., T - 1 \).

3) 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.** Under Assumption 1, there exists a constant \( B_y > 0 \) such that \( \|y_{i,t}\| \) and \( \|\tilde{y}_{i,t}\| \) are both uniformly bounded by \( B_y \). When digging into the updating law \( \ref{25} \), we have \( \|\tilde{\lambda}_{i,t+1}\| = (1 - \epsilon_t)\|\tilde{\lambda}_{i,t} + \gamma \tilde{y}_{i,t}\| \leq (1 - \epsilon_t)\|\tilde{\lambda}_{i,t}\| + \gamma B_y \).

According to \( \ref{22} \) and \( \sum_{i=1}^{N} w_{ij} = 1, \) one might expect \( \|\tilde{\lambda}_{i,t+1}\| = \|\sum_{i=1}^{N} w_{ij}\| \|\tilde{\lambda}_{j,t+1}\| \leq \max(\|\tilde{\lambda}_{i,t+1}\|, \forall i \in 1, ..., N) \). It can be easily verified by mathematical induction that \( \|\tilde{\lambda}_{i,t}\|, \|\tilde{\lambda}_{i,t}\|, \|\tilde{\lambda}_{i,t}\| \leq \gamma B_y \kappa_i/\epsilon_t \). Further we have \( \|s_{i,t}\| \leq [\partial f_{i,t}(u_{i,t})] + \|1_{2}\| \lambda_{i,t} \| \leq C_f + 2\gamma B_y \kappa_i/\epsilon_t \).

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

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

\[
\sum_{t=1}^{T} \frac{1}{2\gamma\kappa_i} \left( \|\tilde{\lambda}_t\|^2 - \|\tilde{\lambda}_{t+1}\|^2 \right) \leq \frac{N}{2\gamma} \left[ \sum_{t=2}^{T} \frac{1}{\kappa_{t-1}} \|\tilde{\lambda}_{t-1}\|^2 + \frac{1}{\kappa_1} \|\tilde{\lambda}_{t-1}\|^2 \right] \tag{30}
\]

\[
< \frac{N}{2} \left[ \sum_{t=2}^{T} \frac{1}{\kappa_{t-1}} + \frac{1}{\kappa_1} \right] \cdot \frac{2\gamma B_y \kappa_T}{\epsilon T} \leq \frac{N\gamma^2 B_y^2 \kappa_T}{2\epsilon T} = O_T(T^{2\beta-\alpha}) \tag{31}
\]

By substituting \( C_f + 2\gamma B_y/\epsilon_t \) for \( \|s_{i,t}\| \), the third term of \( \ref{28} \) becomes

\[
\sum_{t=1}^{T} \frac{\kappa_i}{2} \|s_t\|^2 \leq \sum_{t=1}^{T} \frac{N}{2} \kappa_i (C_f + 2\gamma B_y \kappa_i/\epsilon_t)^2 \]

\[
= \sum_{t=1}^{T} \frac{N}{2} \left[ C_f^2 t^{-\alpha} + 4\gamma C_f B_y t^\beta - 2\alpha + 4\gamma^2 B_y^2 t^{2\beta-3\alpha} \right] \int_1^T t^{1-\alpha} dt + 2N\gamma C_f B_y \int_1^T t^{1+\beta-2\alpha} dt \]

\[
+ 2N\gamma B_y^2 \int_1^T t^{1+2\beta-3\alpha} dt + \text{const}.
\]

\[
= O_T(T^{1+2\beta-3\alpha}) \tag{31}
\]
Hence omitting the less significant terms associated with identical all the time despite going up and down, implying the differently to AGC, owing to their intrinsic heterogeneities, 6. As can be observed from Fig. 5(a) that all BESS contribute effectiveness and features of ORRA with respect to a step is arbitrarily chosen from \([0.2, 0.8]\). For charging and discharging are both 0.95, and the initial SoC capacity is 2 MWh, the peak power is 1 MW, the efficiencies least a path between any two agents \([35]\). For each BESS, the 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 \([35]\). 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 \([0.2, 0.8]\).

### 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 integrated into Area 1, with each assigned 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 \([35]\). 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 of ORRA with respect to a step change. A load increase of 5 MW is introduced to Area 1 at \(t = 10\)s, and the simulation results are given in Fig. 5 and Fig. 6. As can be observed from Fig. 5(a) that all BESS 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 despite going up and down, implying the fairness of allocation during the entire event. In Fig. 5(c), the instantaneous battery usage cost of all nodes is also compared with the result of MATLAB “fmincon” solver to show the near-optimal allocation achieved by ORRA, and only slight inconsistency between \(\sum_{i=1}^{N} f_i(t(u_{i,t}))\) and \(\sum_{i=1}^{N} f_i(t(u_{i,t}^\star))\) is observed (mainly caused by the equality constraint not fully met), which is in line with the regret analysis in Section III.B

Then, the frequency responses of two areas under different configurations are compared in Fig. 6. As outlined, “AIE+BESS”, “ACE+BESS”, and “ACE” respectively correspond to AIE-based AGC with BESS participation (i.e., ORRA), ACE-based AGC with BESS participation, and ACE-based AGC without BESS participation. To avoid confusion, we stress that Fig. 6(a) depicts the frequency deviations of Area 1, and Fig. 6(b) depicts the frequency deviations of Area 2. Compared to the black lines marked with “ACE” and “AIE”, the magnitudes of frequency drops are greatly reduced in the presence of BESS participation due to the capabilities of responding fast and precisely they offered. It is worth noticing that the BESSs may fall into counterproductive regulation, as highlighted in red color, due to the miscalculation of ACE in the presence of bias uncertainty and thus
fail to achieve the AGC performance of the proposed ORRA. 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 implicitly permits a dynamic frequency bias to track with the AFRC and hence mitigates the impact of bias uncertainties, which is fundamentally vital for BESS participation. 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 blue.

**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 total power of five BESSs. Instructed by the AIE signals, the BESSs 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 100s to ramp up to 2.7 MW and there clearly will be a gap in the provision of AGC if there is no BESS participation. Furthermore, the frequency response under ORRA is compared with a benchmark system [9] to illustrate the benefits of BESS participation coordinated by 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 BESSs at a relatively low instantaneous power compared to the CGs can significantly improve AGC performance, and their operation is virtually energy-neutral as the SoC levels are almost kept around their initial values.

**V. Conclusion**

In this paper, two crucial issues regarding BESS participation in AGC are addressed. First, based on online optimization, we have developed a novel scheme termed ORRA to coordinate a group of BESSs providing ramping reserves to CGs to more efficiently participate in AGC. Second, to fully account for the “counteractive regulation” in AGC, the concept of AIE has been leveraged for the design of ORRA. An optimization algorithm has been developed to solve the formulated online optimization problem in an iterative manner, whose sublinear dynamic regret under properly designed learning rates has been rigorously proven. As a result, the proposed ORRA is fully distributed and can guarantee near-optimal and fair allocation in real-time. Simulation studies have been carried out to demonstrate the cost-effectiveness and AGC enhancement of ORRA.

**VI. Appendix**

**A. Proof of Lemma 1**

Proof. According to [19] and \( \sum_{i=1}^{N} h_{i,t}(u_{i,t}^*) = 0 \), we have that \( \text{Reg}(T) = \sum_{t=1}^{T} L_t(u_t, 0_N) - \sum_{t=1}^{T} L_t(u_t^*, \hat{\lambda}_t) \), 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 \(\sum_{t=1}^{T} [L_t(u_t, \mathbf{0}_N) - L_t(u_t, \bar{\lambda}_t)]\) and \(\sum_{t=1}^{T} L_t(u_t, \bar{\lambda}_t) - L_t(u^*_t, \bar{\lambda}_t)\). From updating law (25), we have

\[
\|\lambda_{t+1}\|^2 = \|\lambda_t + (\gamma \kappa t \tilde{y}_t - \epsilon_t \bar{\lambda}_t)\|^2 \\
\leq \|\lambda_t\|^2 + \|\gamma \kappa t \tilde{y}_t - \epsilon_t \bar{\lambda}_t\|^2 + 2(\gamma \kappa t \tilde{y}_t - \epsilon_t \bar{\lambda}_t)\top \lambda_t \\
\leq \|\lambda_t\|^2 + \|\gamma \kappa t \tilde{y}_t - \epsilon_t \bar{\lambda}_t\|^2 + 2\gamma \kappa t \tilde{y}_t \lambda_t.
\]

(35)

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

\[
L_t(u_t, \mathbf{0}_N) - L_t(u_t, \bar{\lambda}_t) \\
\leq \frac{1}{2\gamma \kappa t} \left(\|\lambda_t\|^2 - \|\lambda_{t+1}\|^2\right) + \frac{1}{2\gamma \kappa t} \|\gamma \kappa t \tilde{y}_t - \epsilon_t \bar{\lambda}_t\|^2 \\
+ \|\lambda_t\| \cdot \|\tilde{y}_t - \hat{y}_t\|.
\]

(36)

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

\[
\|u_{t+1} - u^*_t\|^2 \leq \|u_t - u^*_t - \kappa t s_t\|^2 \\
\leq \|u_t - u^*_t\|^2 + \|\kappa t s_t\|^2 - 2\kappa t s_t^\top (u_t - u^*_t).
\]

(37)

By the first-order property of characterization of convex functions, we have \(-2\kappa t s_t^\top (u_t - u^*_t) \leq -2\kappa t [f_t(u_t) - f_t(u^*_t) + (1 - \lambda_t)\top (u_t - u^*_t)]\). 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

\[
L_t(u_t, \bar{\lambda}_t) - L_t(u^*_t, \bar{\lambda}_t) \\
\leq \frac{1}{2\kappa t} \left(\|u_t - u^*_t\|^2 - \|u_{t+1} - u^*_t\|^2\right) + \frac{\kappa t}{2} \|s_t\|^2 \\
+ 2\|u_t\| \cdot \|\bar{\lambda}_t - \bar{\lambda}_t\|.
\]

(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

\[
S(T) = \sum_{t=1}^{T} \frac{1}{2\kappa t} \left(\|u_t - u^*_t\|^2 + \|u_{t+1} - u^*_t\|^2\right) \cdot S_1(T) \\
+ \sum_{t=1}^{T} \frac{1}{2\kappa t} \left(\|u_t - u^*_t\|^2 - \|u_{t+1} - u^*_t\|^2\right) \cdot S_2(T).
\]

(39)

By taking the similar approach alike (30), \(S_1(T)\) can be rearranged as

\[
S_1(T) = \frac{1}{2\kappa t} \|u_t - u^*_t\| - \frac{1}{2\kappa t+1} \|u_{t+1} - u^*_t\| \\
+ \frac{1}{2} \sum_{t=2}^{T} \left(\frac{1}{\kappa t} - \frac{1}{\kappa t-1}\right) \|u_{t-1} - u^*_t\|^2 \\
\leq 2NDB^2_u/\kappa T.
\]

(40)
From $\|x\|^2 - \|y\|^2 \leq (x + y) \cdot (x - y)$, it can be easily seen that

$$S_2(T) = \sum_{t=1}^{T} \frac{1}{2N^2} \left[ (2\|u_{t+1}^{*}\| + \|u_{t+1}^{*}\| + \|u_{t}^{*}\|) \cdot \|u_{t}^{*} - u_{t+1}^{*}\| \right] \leq 2N^2 B_V \nabla V(T).$$

(41)

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

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