Coordinated Scheduling Strategy for Networked Microgrids Preserving Decision Independence and Information Privacy

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With the increasing penetration of distributed renewable generations (DRGs), microgrids will play an important role in the future power system. This paper studies the coordinated scheduling strategy of networked microgrids with private data exchange limitations and local management independence. Based on an adaptive robust optimization method, a coordinated scheduling model of networked systems considering the uncertainty of renewable generations is established. Then distributed algorithms are developed to meet the needs of data privacy protection of individual microgrids. The Augmented Lagrangian (AL) decomposition method decomposes the model into several sub-problems, and an alternate optimization method is developed to speed up the solution. Case studies demonstrate the effectiveness of the proposed model and the solution methods.

Keywords: networked microgrids, robust optimization, distributed renewable generation, dispatching, privacy

INTRODUCTION

To peruse carbo neutrality, various distributed renewable generations (DRGs) are rapidly increasing, and accordingly, microgrids are gaining in importance in countries and regions where the power supply is gradually reducing dependence on traditional energy sources like coal-fired units (Lee et al., 2015; Li X et al., 2016). Microgrids can combine various renewable sources and optimize their use to meet local loads i.e., important buildings and households, etc (Tushar et al., 2014; Martin-Martínez et al., 2016; Zhang and Baillieul, 2016). Moreover, networked microgrids can serve as collaborative distributed systems for enhancing the power system resilience against increasing extreme events (Li et al., 2017; Wang et al., 2016b).

Networked microgrids usually consist of several individuals that correspond to different owners (Gao et al., 2018). Therefore, their operation management systems are independent and only have limited coordination with others. This situation needs to be changed: with the increasing distributed renewable generation integration, it is necessary to develop coordinated dispatching strategy for interconnected microgrids to obtain higher economic and reliable performance (Wang et al., 2016b). Also, the high integration of DRG highlights the importance of coordinating networked microgrids. In order to deal with the DRG uncertainty, each microgrid has to reserve enough spinning reserve capacity (Li et al., 2021). Yet, effective coordination between interconnected microgrids will greatly reduce the reserve capacity level of individual microgrids, since they can share spinning reserves against DRG uncertainty (Chen et al., 2021).

Coordinated dispatching strategy plays a significant role in managing collaborative networked microgrids (Che et al., 2015; Julia and Oliver, 2016; Yuan and Hesamzadeh, 2017). Although traditional centralized dispatching methods for power systems can deal with similar problems, they can hardly address some information issues of individual microgrids (Li et al., 2022a; Li et al., 2022b). Thus, various decomposition techniques have been proposed to solve the coordinated dispatching (Zheng et al., 2013). For example, Lagrangian relaxation (LR) is introduced by adding additional dummy buses (Saber and Venayagamoorthy, 2010; Ghazal et al., 2016), and it decomposes the coordinated dispatching strategy into sever-al sub-problems. Furthermore, the Augmented Lagrangian (AL) decomposition method improves the convergence of the standard LR by introducing a strong convex quadratic penalty (Hu et al., 2016). Also, distributed optimization technologies, such as alternating direction multiplier (ADMM), are used to solve coordinated dispatching in various distributed ways (Lu et al., 2012; Li et al., 2022).

Another noteworthy issue is that how to consider the uncertainty of DRGs. Stochastic optimization (SO) and robust optimization (RO) are typical tools for addressing dispatching problems considering uncertainty of intermittent power (Wang et al., 2014; Zheng et al., 2015; Ban et al., 2021; Mansour-Saatloo et al., 2020). For instance, an SO model is introduced to provide a probability guarantee for the solution in (Li S et al., 2016; Liu et al., 2016). However, these models rely on the accuracy of random scenes and their probability of realization. Instead of using random scenes, RO model uses uncertainty sets to capture randomness (Janak et al., 2007; Siddiqui et al., 2015). Then, solving the RO problem is to find an optimal scheme that is not affected by any disturbance within the uncertainty set (Lin et al., 2004; Parisio et al., 2012; Yuan et al., 2016). Due to its advantages, RO has been employed in optimal scheduling to handle the uncertainty. However, there are few reports on employing RO in decentralized scheduling that considers decision independence and information privacy to handle the uncertainty in net-worked microgrids (Mármol et al., 2012; Yang et al., 2019).

This work focuses on the impact of DRG uncertainty on coordinated dispatching strategy for interconnected microgrids with high penetration distributed renewable generations. It formulates the problem in a distributed way and the proposed framework can preserve information privacy and management independence of individual microgrids. A two-stage robust optimization scheme establishes a decentralized coordinated scheduling model with uncertain DRGs, and the AL method is employed to decompose the scheduling model into several easy-solving sub-problems, which will speed up the solution of the problem in a decentralized way.

PROBLEM FORMULATION

This section presents the framework of networked microgrids, and then it raises the formulation of the proposed optimization model by introducing the coordinated dispatching strategy preserving decision independence and information privacy.

Framework of Networked Microgrids

Due to the large-scale integration of intermittent DRGs, future power systems will be very different from traditional ones. For example, networked microgrids will play an increasing important role in future energy supply to hedge against the uncertainties of DRGs. As shown in **Figure 1**, each microgrid has its own decisions and objectives. And accordingly, each microgrid is equipped with a local manager (LM) that provides control and monitoring of local DRGs, distributed generations (DGs) and loads. Besides, each LM is also responsible for determining power exchanges with the others, on/off states of DGs, and charging/discharging states of energy storage systems.

In energy management, individual microgrids intend to independently obtain a robust strategy to avoid the risk from uncertainties of renewables and loads while keeping their data private. In this setting, this paper studies a model that considers two stages, i.e., the first one considers the joint scheduling of on/off states of generation units and tie-line power, and the second one considers the dispatch with uncertain DRG power. Accordingly, the decision variables mainly include the DRG power, storage charge/discharge power, and exchange power, etc. The exchange power represents the coordination among individual microgrids, which is decided in a decentralized way to preserve the decision independence and information privacy.

Objective

The objective, see **Eq. 1**, is to minimize the total cost of the optimal scheduling. The cost includes 1) the de-cision-making cost of traditional generation units in stage I and 2) the dispatch cost considering the worst-case of DRGs in stage II.

$$\min_{\chi_m^{\mathrm{I}} \in \Omega_m^{\mathrm{I}}} \sum_{m \in NM} \left\{ f_m^{\mathrm{I}} \left(\chi_m^{\mathrm{I}}, \boldsymbol{P}_m^{\mathrm{R}*} \right) + \max_{\boldsymbol{P}_m^{\mathrm{R}} \in \boldsymbol{U}_m^{\mathrm{R}}} \left[\min_{\chi_m^{\mathrm{II}} \in \Omega_m^{\mathrm{II}}} f_m^{\mathrm{II}} \left(\chi_m^{\mathrm{II}}, \boldsymbol{P}_m^{\mathrm{R}} \right) \right] \right\} \quad (1)$$

where $f^{\mathrm{I}} m (*)$ and $f^{\mathrm{II}} m (*)$ are total on/off cost function and total economic dispatch cost function of microgrid m, $\chi\mathrm{I}\, m$ and $\chi\mathrm{II}\, m$ represent decision variable vector of stages I and II, $\boldsymbol{P}_m^{\mathrm{R}*}$ and $\boldsymbol{P}_m^{\mathrm{R}}$ represent vector of forecasted and available DRG power, $\Omega\mathrm{I}\, m$ and $\Omega\mathrm{II}\, m$ are feasible sets of decision variables of microgrid m in stages I and II, $\boldsymbol{Y}_m^{\mathrm{R}}$ is uncertainty set of available DRG power of microgrid m, and NM is the set of microgrids.

Objective in Stage I

The decision variables in stage I involves the scheduling of generator units and connection lines in individual microgrids.

$$\chi_m^{\mathrm{I}} = \left\{ I_{g,t}^{\mathrm{DG}}, X_{g,t}^{\mathrm{DG}}, Y_{g,t}^{\mathrm{DG}}, \alpha_{m,i,t} \;\; \forall g \in NG_m, i \in NB_m \cup NB_m^{**}, t \in NT \right\} \quad (2)$$

where $IG\, g,t$ is binary variable that is equal to 1 if generation unit g is on at period t and 0 otherwise, $XG\, g,t$ is binary variable that is equal to 1 if generation unit g is started up at period t and 0 otherwise, $YG\, g,t$ is binary variable that is equal to 1 if generation unit g is started down at period t and 0 otherwise, $\alpha_{m,i,t}$ is phase angle variable of boundary bus i at period t perceived by microgrid m, g and NG_m are indices and set of generation units in microgrid m, NB_m and $NB^{**}m$ are the set of indices
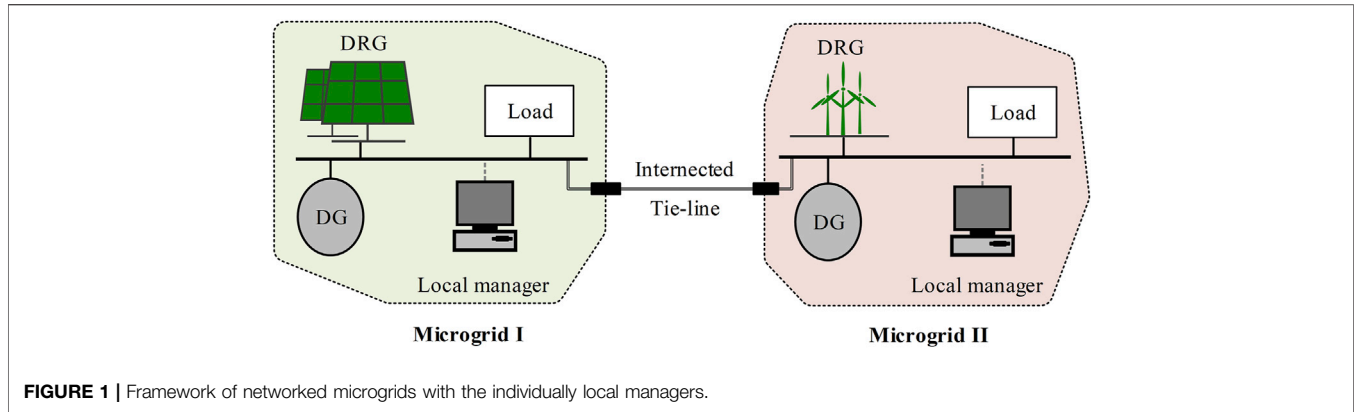
FIGURE 1 | Framework of networked microgrids with the individually local managers.

of connection buses in microgrid m and the set of indices of others connection buses connected to microgrid m, t and NT are indices and set of periods, respectively.

The costs associated with the first stage which includes startup costs, shutdown costs, and no-load costs of traditional units, which are as

$$f_m^{\mathrm{I}}(\chi_m^{\mathrm{I}}, \boldsymbol{P}_m^{\mathrm{R*}}) = \sum_{t \in NT} \sum_{g \in NG_a} \left(c_g^{\mathrm{ON}} X_{g,t}^{\mathrm{DG}} + c_g^{\mathrm{OFF}} Y_{g,t}^{\mathrm{DG}} + c_g^{\mathrm{ND}} I_{g,t}^{\mathrm{DG}} \right) \quad (3)$$

where c_g^{ON}, c_g^{OFF} and c_g^{ND} are startup and shutdown cost, and non-load cost of generation unit g, respectively.

Objective in Stage II
The decision variables in stage II include the generation scheduling of conventional units and renewables, and the phase angles of the internal buses in microgrid m.

$$\chi_m^s = \left\{ P_{g,t}^{\mathrm{G}}, P_{g,t}^{\mathrm{UP}}, P_{g,t}^{\mathrm{DOWN}}, P_{r,t}^{\mathrm{R}}, \theta_{i,t} \quad \forall t \in NT, g \in NG_m, r \in NR_m, i \in NG_m^{\mathrm{I}} \right\}$$

where $PG\ g,t$ is generation output of conventional generation unit g at period t, $P_{g,t}^{\mathrm{UP}}/P_{g,t}^{\mathrm{DOWN}}$ is upward/downward reserve capacity of generation unit g at period t, $PR\ r,t$ is generation output of renewable unit r at period t, and $\theta_{i,t}$ is the phase angle of internal bus i at period t.

The dispatch cost associated with stage II is as

$$f_m^{\mathrm{II}}(\chi_m^{\mathrm{II}}, \boldsymbol{P}_m^{\mathrm{R}}) = \sum_{t \in NT} \left[\sum_{g \in NG_m} f_g^{\mathrm{G}}(P_{g,t}^{\mathrm{G}}) + \sum_{\forall r \in NR_m} c_r \left(P_{r,t}^{\mathrm{R}} - P_{r,t}^{\mathrm{R*}} \right) \right] \quad (4)$$

where f_g^{G} is piecewise linear cost of generation unit g, c_r is penalty price of renewable generation curtailment r.

This paper describes the randomness of DRGs with an uncertainty set, which is compiled using a typical uncertainty budget set (Bertsimas and Sim, 2004). The uncertainty set is defined using a typical uncertainty budget set, and it benefits flexible adjusting the conservativeness of the robust solution with different level of uncertainty set $\Omega_{\mathrm{R}\ m}$, which is defined as

$$\tilde{P}_{r,t}^{\mathrm{R}} = P_{r,t}^{\mathrm{R*}} + \left(\tilde{P}_{r,t}^{\mathrm{R}} - P_{r,t}^{\mathrm{R*}} \right) z_{r,t}^{\mathrm{R+}} - \left(P_{r,t}^{\mathrm{R*}} - \underline{P}_{r,t}^{\mathrm{R}} \right) z_{r,t}^{\mathrm{R-}} \quad \forall t \in NT, r \in NR_m \quad (5)$$

where the auxiliary variables are defined as

$$\left\{ z_{r,t}^{\mathrm{R+}}, z_{r,t}^{\mathrm{R-}} \,\middle|\, \sum_{t \in NT} \left(z_{r,t}^{\mathrm{R+}} + z_{r,t}^{\mathrm{R-}} \right) \leq \Gamma_r, 0 \leq z_{r,t}^{\mathrm{R+}}, z_{r,t}^{\mathrm{R-}} \leq 1 \,\, \forall t \in NT, r \in NR_m \right\} \quad (6)$$

Constraints
Constraints for Stage I
The variable set χ^{I} is in the feasible region of stage I, hereafter refer as Ω^{I}, and its constraints are defined as

$$\begin{cases} \chi_{i*,i,t} = \chi_{j*,i,t} \,\, \forall (i,j) \in \varepsilon^{\mathrm{tie}}, i > j, t \in NT \\ \chi_{i*,j,t} = \chi_{j*,j,t} \,\, \forall (i,j) \in \varepsilon^{\mathrm{tie}}, i > j, t \in NT \end{cases} \quad (7)$$

$$\chi_{m*,\mathrm{ref},t} = 0 \quad \forall m* \in \Phi(\mathrm{ref}), t \in NT \quad (8)$$

$$\begin{cases} \dfrac{\left| \chi_{i*,i,t} - \chi_{i*,j,t} \right|}{Z_{i,j}} \leq \bar{P}_{i,j} \quad \forall (i,j) \in \varepsilon^{\mathrm{tie}}, i > j, t \in NT \\[4mm] \dfrac{\left| \chi_{j*,i,t} - \chi_{j*,j,t} \right|}{Z_{i,j}} \leq \bar{P}_{i,j} \quad \forall (i,j) \in \varepsilon^{\mathrm{tie}}, i > j, t \in NT \end{cases} \quad (9)$$

$$I_{g,t}^{\mathrm{DG}} - I_{g,t-1}^{\mathrm{DG}} = X_{g,t}^{\mathrm{DG}} - Y_{g,t}^{\mathrm{DG}} \,\, \forall g \in NG_m, t \in NT \quad (10)$$

$$\begin{cases} \displaystyle\sum_{\tau = \max\{1, t-T_g^{\mathrm{ON}}+1\}}^{t} X_{g,\tau}^{\mathrm{DG}} \leq I_{g,\tau}^{\mathrm{DG}} \,\, \forall g \in NG_m, t \in NT \\[4mm] \displaystyle\sum_{\tau = \max\{1, t-T_g^{\mathrm{OFF}}+1\}}^{t} Y_{g,T}^{\mathrm{G}} \leq 1 - I_{g,t}^{\mathrm{DG}} \,\, \forall g \in NG_m, t \in NT \end{cases} \quad (11)$$

$$I_{g,t}^{\mathrm{DG}}, X_{g,t}^{\mathrm{DG}}, Y_{g,t}^{\mathrm{DG}} \in \{0,1\} \,\, \forall g \in NG_m, t \in NT \quad (12)$$

where (7) is the phase angle coupling constraint of the tie line amongst microgrids, (8) sets the phase angle of the reference bus as 0, (9) limits the tie-line capacity, (10) is the logical constraints on the status of the units, (11) is the minimum up/down time limits of the generator set, and (12) defines the feasible sets of the first stage variables.

Constraints for Stage II
The feasible set Ω_m^{II} of decision-making in the second stage of microgrid m is as

$$\sum_{j\in\Theta_a^{\mathrm{I}}(i)}\frac{\theta_{i,t}-\theta_{j,t}}{Z_{i,j}}+\sum_{j\in\Theta_m^{\mathrm{B}}(i)}\frac{\theta_{i,t}-\alpha_{m,j,t}}{Z_{i,j}}$$

$$=\sum_{g\in\Theta_m^{\mathrm{G\cup R\cup D}}(i)}\left(\underline{P}_g^{\mathrm{G}}I_{g,t}^{\mathrm{G}}+P_{g,t}^{\mathrm{G}}+P_{r,t}^{\mathrm{R}}-P_{d,t}^{\mathrm{D}}\right)\forall t, i\in NI_m \quad (13)$$

$$\sum_{j\in\Theta_a^{\mathrm{I}}(i)}\frac{\alpha_{m,i,t}-\theta_{j,t}}{Z_{i,j}}+\sum_{j\in\Theta_m^{\mathrm{B}}(i)}\frac{\alpha_{m,i,t}-\alpha_{m,j,t}}{Z_{i,j}}$$

$$=\sum_{g\in\Theta_m^{\mathrm{G\cup R\cup D}}(i)}\left(\underline{P}_g^{\mathrm{G}}I_{g,t}^{\mathrm{G}}+P_{g,t}^{\mathrm{G}}+P_{r,t}^{\mathrm{R}}-P_{d,t}^{\mathrm{D}}\right)\forall t, i\in NI_m \quad (14)$$

$$\left|\frac{\theta_{i,t}-\theta_{j,t}}{Z_{i,j}}\right|\le\bar{P}_{i,t}\ \ \forall i\in NB_m, j\in\Theta_m^{\mathrm{I}}(i), j>i \quad (15)$$

$$\left|\frac{\theta_{i,t}-\alpha_{m,j,t}}{Z_{i,j}}\right|\le\bar{P}_{i,t}\ \ \forall i\in NB_m, j\in\Theta_m^{\mathrm{I}}(i) \quad (16)$$

$$0\le P_{r,t}^{\mathrm{R}}\le\bar{P}_{r,t}^{\mathrm{R}}\ \forall t, r\in NR_m, m\in NM \quad (17)$$

where (13) and (14) are the DC power flow constraints of buses, (15) and (16) are the internal transmission line capacity constraints, (17) represents the power generation capacity of DRGs. Note that the other typical constraints including ramping up/down limits, generation limits, system spinning/operation reserve requirements, regulation up/down requirements, regulation down requirement are not listed in this paper, and interested readers are referred to (Ban et al., 2017) and (Wang et al., 2008) for more details.

SOLUTION METHOD

`This section introduces the solution method for the formulated problem. Firstly, the AL decomposition method de-composes the model into several simple problems for individual microgrids, and the standard ADMM algorithm is used to solve it. Secondly, the independent sub-problems are solved by the column constraint generation (C&CG) method. Thirdly, a heuristic method is developed to alleviate the solution complexity by obtaining a suboptimal solution in limited iterations.

Augmented Lagrangian Decomposition Method and Alternating Direction Multiplier Algorithm

The AL relaxation of microgrid m is formulated by relaxing the coupled constraints (6) and (7), and it gets

$$L_m\left(\chi_m^{\mathrm{I}},\lambda_m,\bar{\alpha}\right)=c_m^{\mathrm{I}}\left(\chi_m^{\mathrm{I}},P_m^{\mathrm{N*}}\right)+\max_{\tilde{P}_m^{\mathrm{N}}\in\Omega_m^{\mathrm{N}}}\min_{\chi_m^{\mathrm{II}}\in\Omega_m^{\mathrm{II}}}c_m^{\mathrm{II}}\left(\chi_m^{\mathrm{II}},\tilde{P}_m^{\mathrm{N}}\right)$$

$$+\sum_{i\in N_m^{\mathrm{B}}\cup N_m^{'\mathrm{B}},t\in NT}\left[\lambda_{m,i,j}\left(\alpha_{m,i,t}-\bar{\alpha}_{i,t}\right)+\frac{\rho}{2}\left(\alpha_{m,i,t}-\bar{\alpha}_{i,t}\right)^2\right]$$

$$=c_m^{\mathrm{I*}}\left(\chi_m^{\mathrm{I}},\lambda_m,\bar{\alpha}\right)+\max_{\tilde{P}_m^{\mathrm{N}}\in\mathrm{U}_m^{\mathrm{R}}}\left[\min_{\chi_m^{\mathrm{II}}\in\Omega_m^{\mathrm{II}}}c_m^{\mathrm{II}}\left(\chi_m^{\mathrm{II}},\tilde{P}_m^{\mathrm{N}}\right)\right]$$

$$(18)$$

where $\lambda_{m,i,t}$ is the dual variable corresponding to the difference between phase angle of boundary bus i perceived by microgrid m (i.e., $\alpha_{m,i,t}$) and the average phase angle of

boundary bus i perceived by its connecting microgrids (i.e., $\bar{\alpha}_{,i,t}$). $\lambda_{m,i,t}$ reflects the shadow prices of boundary-bus angles between different microgrids. $\bar{\alpha}_{,i,t}$ is the average angle perceptual value of all lines connected to boundary bus i, and it is expressed as

$$\bar{\alpha}_{i,t}=\sum_{m\in\Xi_i}\frac{\alpha_{m,i,t}}{|\Xi_i|}\ \forall t, i\in NI_m \quad (19)$$

where Ξ_i is the set of the microgrids connected to the bus, and $|\Xi_i|$ indicates the total number of microgrids connected to bus i.

The sub-problem of microgrid m (i.e., SP_m) can be solved using its augmented Lagrangian relaxation.

$$SP_m\ \ \min\{L_m\left(\chi_m^{\mathrm{I}},\lambda_m,\bar{\alpha}\right)\big|\chi_m^{\mathrm{I}}\in\Omega_m^{\mathrm{I}},\text{constraints (9)}$$

$$-\text{(13)},\forall g\in NG_m, t\in NT\} \quad (20)$$

The ADMM algorithm solves the sub-problem. In the solution framework, each microgrid only exchanges the phase angles of boundary buses with its neighbors in a decentralized way. Accordingly, the privacy of individuals can be fully preserved. Detailed solution method is given in **Figure 2**, and it mainly includes 6 steps, namely initialization, exchanging information, updating perception, subproblem computation, checking convergence, and updating dual variables. Individuals only exchanges boundary information (i.e., the phase angles of the boundary buses) with the others, and accordingly, this distributed algorithm protects information privacy when individuals managing their own decisions, also it contributes to promoting the development of underlying electricity market.

Solving Sub-problems

The C&CG algorithm solves the sub-problems (Zeng and Zhao, 2013). Similar to other decomposition methods, the C&CG method separates the original problem to a master one, i.e., MP_m, and several sub-problems, i.e., BSP_m. And the master problem and sub-problems are defined as

$$MP_m\quad\min_{\chi_m^{\mathrm{I}}=\Xi_m^{\mathrm{II}(t)},\varsigma}\left\{c_m^{\mathrm{I*}}\left(\xi_a^f,\lambda_a^{(m)},\bar{\alpha}_a^{(m)}\right)+\varsigma\big|\Phi\right\}$$

$$\Phi=\left\{\begin{array}{l}\chi_m^{\mathrm{I}}\in\Omega_m^{\mathrm{I}},\Xi_m^{\mathrm{II}(t)}=\left[\chi_m^{\mathrm{II}(1)},\chi_m^{\mathrm{II}(2)},\cdots,\xi_m^{\mathrm{II}(L)}\right],\varsigma\ge c_m^{\mathrm{II}}\left(\chi_m^{\mathrm{II}(l)},\tilde{P}_m^{\mathrm{R*}(l)}\right),\\\chi_m^{\mathrm{II}(l)}\in\Omega_m^{\mathrm{II}}\left(\chi_m^{\mathrm{II}},\tilde{P}_m^{\mathrm{R*}(l)}\right),\ \forall l=1,2,\ldots,L\end{array}\right\}$$

$$BSP_m\quad Q_a\left(\chi_m^{\mathrm{I*}}\right)=\max_{\tilde{P}_m^{\mathrm{R}}\in\Omega_m^{\mathrm{R}}}\left[\min_{\chi_m^{\mathrm{II}}\in\Omega_m^{\mathrm{II}}}c_m^{\mathrm{II}}\left(\chi_m^{\mathrm{II}},\tilde{P}_m^{\mathrm{R}}\right)\right]$$

The employed C&CG solution process is shown in **Figure 3**, which mainly includes 5 steps, namely initialization, solve the master problem MP_m, solving the subproblem BSP_m, checking convergence, generating constraints and columns.

Heuristic Solution Method

Since the standard ADMM can hardly guarantee the solution convergence of the proposed problem, a heuristic method is employed to improve the solution performance. The details are given as follows.

FIGURE 2 | Flowchart of the employed ADMM.

FIGURE 3 | Flowchart of the subproblems.
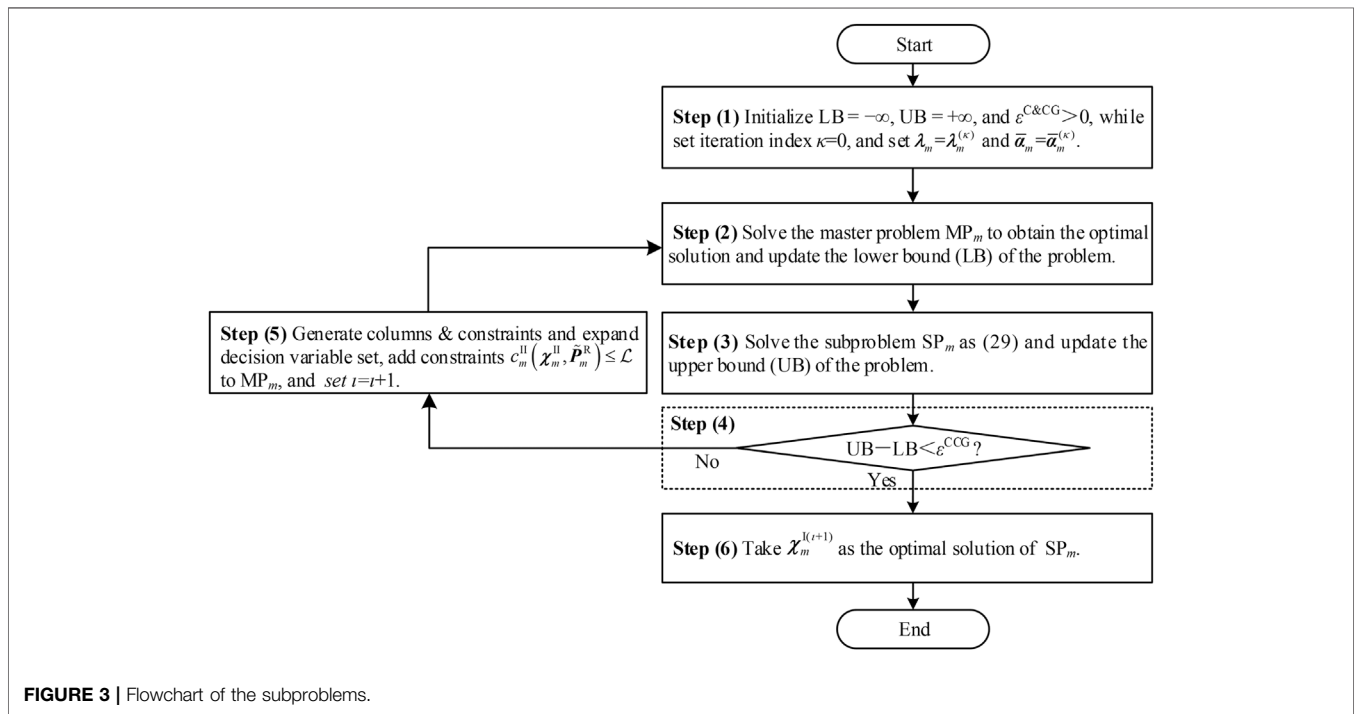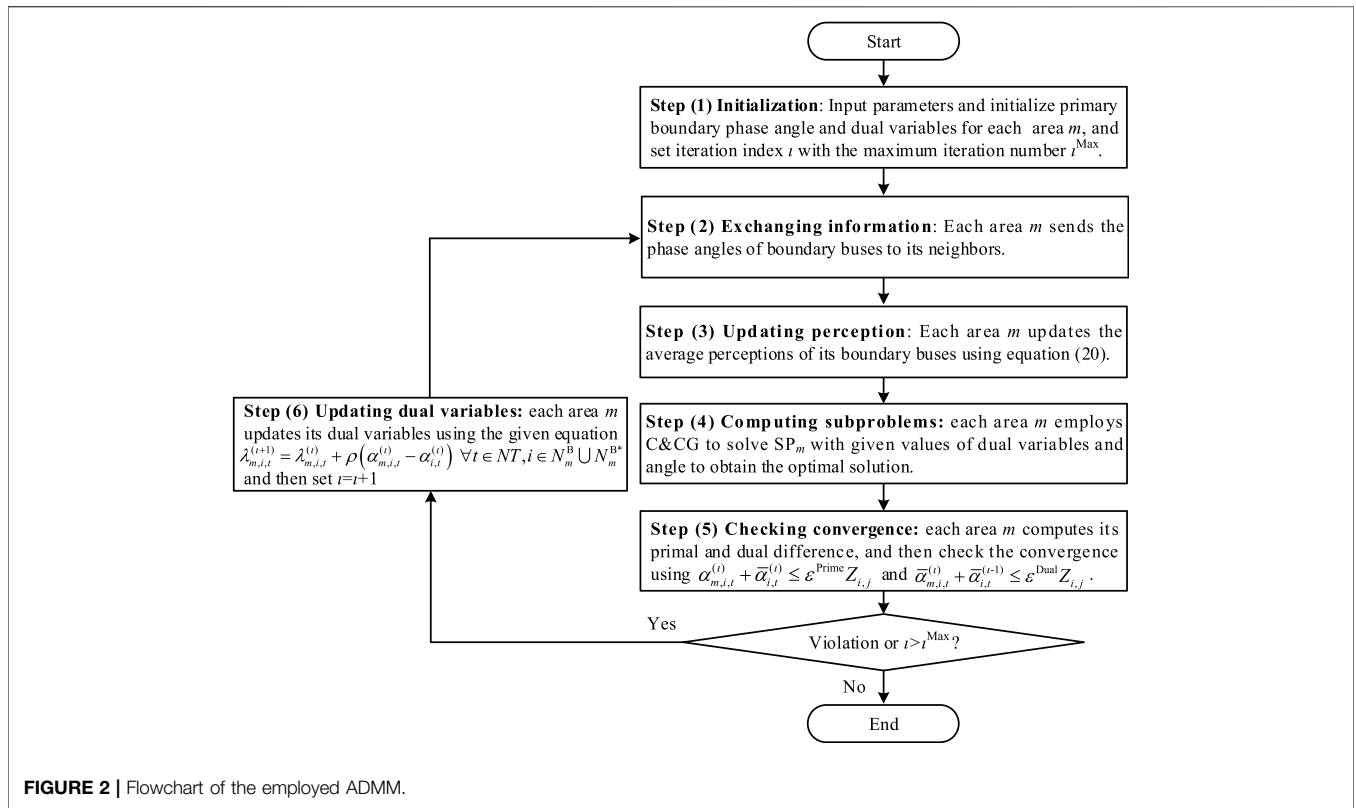
Firstly, set the variables IG g,t as continuous variables ranging from 0 to 1 and relax the corresponding integrality constraints. Accordingly, a relaxed version of the model is obtained. The relaxed one is equivalent to a linear programming with multiple scenarios, and then it can be solved by the ADMM, which ensures the convergence for

linear programs. The continuous relaxation is solved to provide initial values of boundary-bus phase angles $\alpha_{m^*,i,t}^0$ for the iteration loop with iteration time index $\iota = 0$.

Secondly, it optimizes the unit commitment problem when the phase angles of the boundary buses are fixed, namely

$$\alpha_{m,i,t} = \alpha_{i,t}^\iota = \sum_{m \in \Theta_i} \frac{\alpha_{m^*,i,t}^\iota}{|\Theta_i|} \; \forall t \in NT, m \in NG_m, i \in N_m^B \cup N_m^{B^*} \quad (21)$$

where $\alpha_{m^*,i,t}^{(\iota)}$ represents the last solution. Under fixed conditions, the original problem is decomposed into the following regional sub-problems

$$\text{BSP}_m^* \quad \min \; c_m^{\mathrm{I}}\left(\boldsymbol{\chi}_m^{\mathrm{I}}, \boldsymbol{P}_m^{\mathrm{R}^*}\right) + \max_{\tilde{P}_m^{\mathrm{R}} \in U_m^{\mathrm{R}}} \left[\min_{\boldsymbol{\chi}_m^{\mathrm{II}} \in \Omega_m^{\mathrm{II}}} c_m^{\mathrm{II}}\left(\boldsymbol{\chi}_m^{\mathrm{II}}, \tilde{\boldsymbol{P}}_m^{\mathrm{R}}\right) \right] \boldsymbol{\chi}_m^{\mathrm{I}} \in \Omega_m^{\mathrm{I}} \quad (22)$$

The above problem is an adaptive robust problem with a given tie-line power flow. In the case of similar structures, the C&CG algorithm is used to solve finite convergence. The optimal solutions $I_{g,t}^{\mathrm{G}}$, $X_{g,t}^{\mathrm{G}}$ and $Y_{g,t}^{\mathrm{G}}$ are denoted by $I_{g,t}^{\mathrm{G}(\iota)}$, $X_{g,t}^{\mathrm{G}(\iota)}$ and $Y_{g,t}^{\mathrm{G}(\iota)}$ respectively.

Thirdly, if the binary variable set has not changed in iteration ι, namely

$$I_{g,t}^{\mathrm{G}(\iota)} = I_{g,t}^{\mathrm{G}(\iota-1)}, X_{g,t}^{\mathrm{G}(\iota)} = X_{g,t}^{\mathrm{G}(\iota-1)}, Y_{g,t}^{\mathrm{G}(\iota)} = Y_{g,t}^{\mathrm{G}(\iota-1)} \;\; \forall t \in NT, g \in NG_m \quad (23)$$

then binary variables $I_{g,t}^{\mathrm{G}}$, $X_{g,t}^{\mathrm{G}}$, and $Y_{g,t}^{\mathrm{G}}$ are taken as the final solution, otherwise, set $\iota = \iota+1$ and go to the next iteration.

Lastly, it optimizes the phases angles of the boundary buses when the obtained binary states of generation units, i.e., $I_{g,t}^{\mathrm{G}}$, $X_{g,t}^{\mathrm{G}}$, $Y_{g,t}^{\mathrm{G}}$, are fixed. Note that the original problem becomes a linear one, which can be easily solved using the standard ADMM algorithm. In this way, the original problem is largely simplified while ensuring the solution accuracy.

CASE STUDY AND DISCUSSION

All simulations are run on a PC with implemented with MATLAB R2014a at Intel Core i7-4600U 2.10 GHz with 8 GB memory. The related MILP and mixed integer quadratic programming (MIQP) problems are solved by Gurobi 9.0.A.

Parameters

Case studies were carried out on the system consisting of two microgrids. As shown in **Figure 4**, the system involves two microgrids, connected by a tie-line. The studied DRG is integrated into microgrid II.

The hourly forecast value and forecast interval of renewable generation are shown in **Figure 5**. The upper and lower limits represent the uncertain set. It is assumed that the system operating reserve, spinning reserve and regulation are 10, 5 and 2% of the system load, respectively. And the parameters are set as follows. The uncertainty budget, i.e., Γ, is 12. The penalty factor of the ADMM is 0.5. The penalty factor of the ADMM program is the convergence tolerance of the original residue and the dual residue of the ADMM program. The maximum number of the iterations of
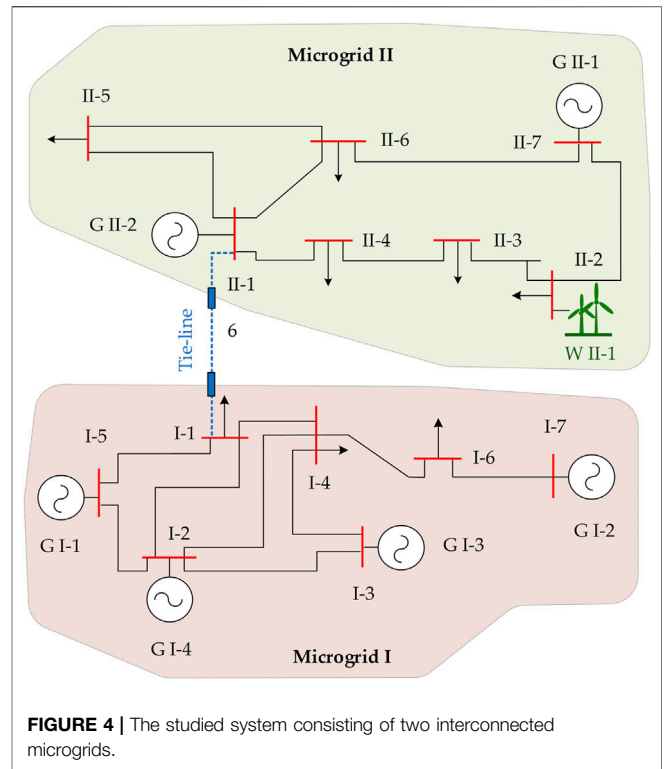

FIGURE 4 | The studied system consisting of two interconnected microgrids.

is set as 200. The relative convergence tolerance of the C&CG program is 0.05%. The subproblems were solved with the MIP and MIQP solvers, and the relative gap tolerances are set to 0.1%. And the other key parameters of units, transmission lines, and hourly load are listed in **Tables 1**, **2**, **3**, respectively.

Solution Process

The solution method in Section 3 was used to solve the problem. **Figures 6**, **7** illustrate the solution process. **Figure 6** shows the maximum solution gap as a function of the iterations. The maximum gap is decreased to the defined tolerance in 60 iterations. Meanwhile, **Figure 7** shows the maximum tie-line power gap converging to a coincided value indicating that the solution succeeds.

In the solution process, the continuous relaxation is solved by the ADMM. The process continues till the primal and dual residues at each ADMM iteration converges to predefined values. Then in the iteration loop of the heuristic solution method, see **Section 3.3**, the boundary phase angles were fixed to solve the other part of the problem by the C&CG procedure, see **Section 3.2**, to obtain on/off states of DGs. Accordingly, the binary variables were fixed. Again, the binary-fixed problem was solved by the ADMM, and another heuristic solution method was started. If the binary solutions of the problem were the same as their previous values, then the solution terminates; otherwise, the solution process will continue.

To further verify the effectiveness of the proposed solution methods, the problem was re-solved in a centralized way with identical parameters, and the results were compared. It shows that the results of the employed approaches are very close to those of the centralized method. For example, the commitment
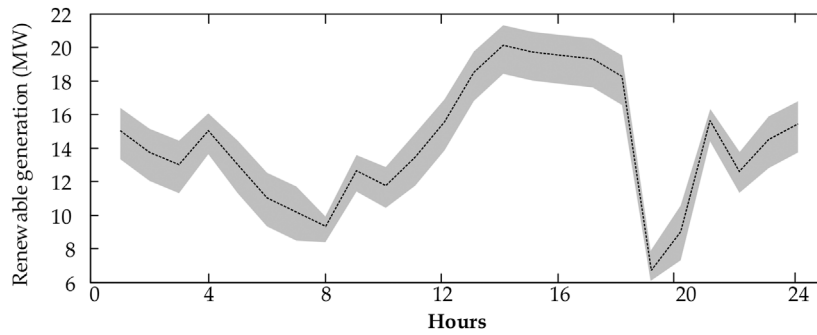
FIGURE 5 | The forecast value and interval of renewable generation.

TABLE 1 | Parameters of generation units.

机组编号	Fuel cost function				Generation Limits		Ramp	
	a_i (t/MW^{2}h)	b_i (t/MWh)	c_i (t/h)	γ_i ($/t)	$p_{i,max}$ (MW)	$p_{i,min}$ (MW)	ru_i (MW/h)	rd_i (MW/h)
G I-1	0.0289	0.12643	5.2	70.71	36	8	12	12
G I-2	0.0289	0.12643	5	68.53	38	10	12.5	12.5
G I-3	0.0263	0.15318	4	67.43	29	7.5	8	8
G I-4	0.0289	0.15785	4.7	70.16	28	11	8	8
G II-1	0.0232	0.16715	3.9	69.47	18	5	7.5	7.5
G II-2	0.0382	0.17166	3.2	72.52	12	2.5	6	6

TABLE 2 | Parameters of transmission lines.

Line No	From Bus	To Bus	X (p.u.)	Flow Limit (MW)
1	I-5	I-2	0.170	25.0
2	I-5	I-1	0.258	18.0
3	I-2	I-3	0.150	17.5
4	I-2	I-4	0.197	18.5
5	I-2	I-1	0.140	22.5
6	I-3	I-4	0.018	32.0
7	I-4	I-1	0.037	17.5
8	I-4	I-6	0.037	19.5
9	II-1	II-4	0.197	25.0
10	II-1	II-5	0.197	15.0
11	II-1	II-6	0.150	18.0
12	I-6	I-7	0.140	28.0
13	II-2	II-3	0.039	17.5
14	II-2	II-7	0.037	17.8
15	II-3	II-4	0.152	25.0
16	II-5	II-6	0.183	15.0
17	II-6	II-7	0.192	26.0
Tie-line	I-1	II-1	0.187	42.5

TABLE 3 | Parameters of hourly load.

Hours	Bus No							
	I-4	I-1	I-6	II-2	II-3	II-4	II-5	II-6
1	19	11.3	8.40	9.80	9.40	17.7	10.7	5.5
2	20.4	12.1	9	10.6	10.1	19	11.5	5.9
3	20.4	12.1	9	10.5	10	19	11.5	5.9
4	20.5	12.2	9	10.6	10.1	19.1	11.6	5.9
5	20.7	12.3	9.1	10.7	10.2	19.3	11.7	6
6	21.2	12.6	9.3	11	10.5	19.7	11.9	6.1
7	23.7	14.1	10.4	12.3	11.7	22.1	13.4	6.9
8	25.2	15	11.1	13	12.4	21.6	14.2	7.3
9	23.6	14.6	10.8	12.7	12.1	22.5	13.9	7.1
10	23.4	13.5	10	11.7	11.1	22.8	13.7	7
11	26.8	14.5	12.2	13.4	13.7	22.1	15.6	7.4
12	25.5	14.9	12.5	13.7	14	24.7	16	6.9
13	26.3	14.8	12.5	12.6	14	23.6	15.4	7.3
14	26.1	13.7	12.4	13.5	13.9	23.4	15.8	7.5
15	26.4	12.9	12.5	13.7	14	23.6	15.4	6.6
16	25	11.8	11	12.9	12.3	22.3	14.1	7.2
17	22.6	11.4	9.9	11.7	11.1	22	12.7	6.5
18	21.4	12.7	9.4	11.1	10.6	19.9	12.1	6.2
19	24.6	13.6	10.8	12.7	12.1	22.9	16.6	8.5
20	20.6	12.2	9.1	10.7	10.2	19.2	11.6	6
21	21.1	12.6	9.3	10.9	10.4	19.7	11.9	6.1
22	24.6	14.6	10.8	12.7	12.1	22.9	13.8	7.1
23	19.7	11.7	8.7	10.2	9.7	18.4	11.1	5.7
24	19.2	11.4	8.4	9.9	9.5	17.8	10.8	5.5

states of the former one are identical to the solutions of the latter one, except that the smallest generation unit G II-2 is additionally committed by the proposed method at hours 4 and 5 h and the tie-line flow of them show some differences. Although these differences indicate the suboptimality of the proposed methods, the optimal quality of the employed solution is highly satisfactory. For instance, the objective value, i.e., the total cost, of the latter one is $ 47,050, which is slightly lower than that of the employed ones ($ 47,120) by 0.12%.

The computation time is 76 s of paralleled CPU time, which is the sum of computation time of regional subproblems in each iteration. It also shows that in cases with small budgets,

FIGURE 6 | Evolution of the maximum solution gap.

FIGURE 7 | Evolution of the maximum tie-line flow gap.

FIGURE 8 | Hourly dispatch results of the generators.
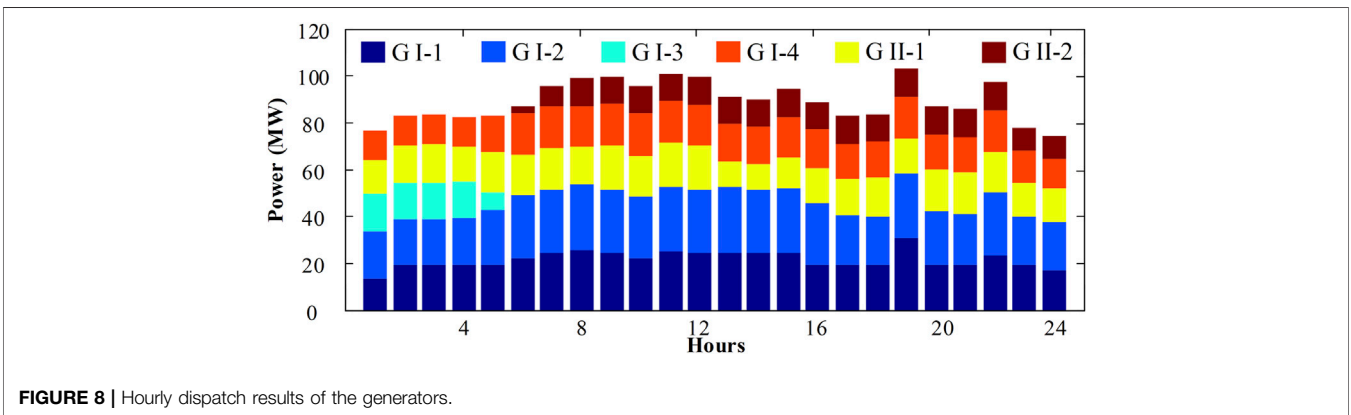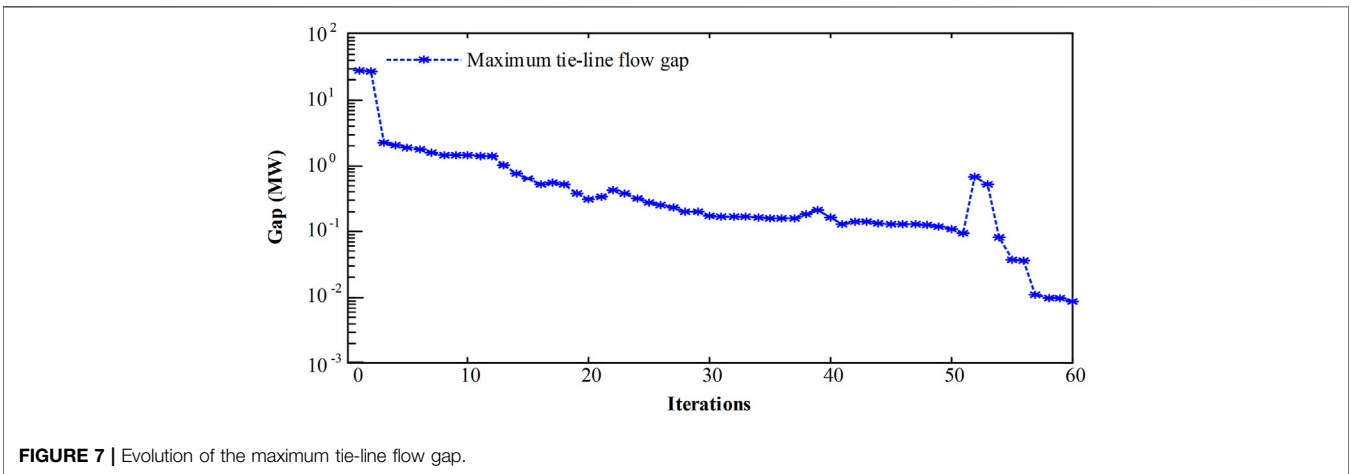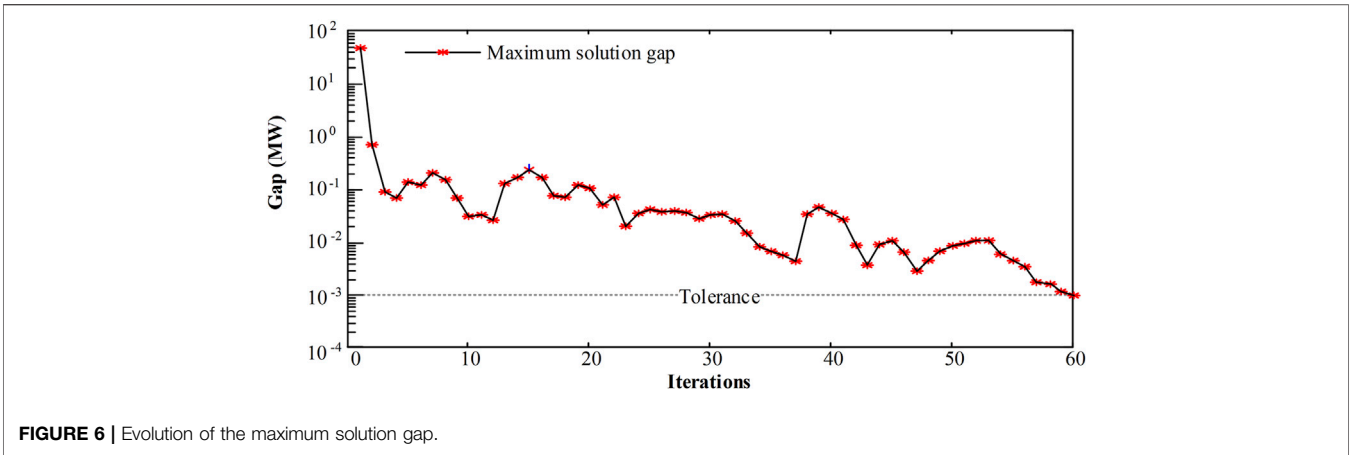
the solution methods typically take more computational time. However, the computation burden is acceptable in practical cases. The proposed method is developed to solve that preserve decision independence and information privacy in a fully decentralized manner, rather than competing with the centralized method in computational efficiency. It is worthy

noted that the developed decentralized method, protecting decision-making independence and information privacy, deserve more research on its computational efficiency, which will be a key part of our future work.

Moreover, a modified IEEE 118-bus system is used to analyze the proposed solution approach. It involves 76 units, 186 branches,
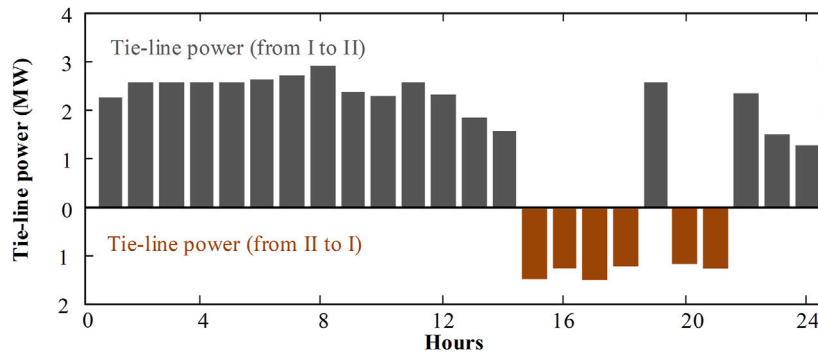
FIGURE 9 | Profiles of the hourly tie-line power components.

TABLE 4 | Parameters of the introduced energy storage.

| Item | $p^{ch}_{s,max}/p^{dis}_{s,max}$ | $p^{ch}_{s,min}/p^{dis}_{s,min}$ | $E_{s,0}$ | ΔE_s | $E_{s,min}$ | $E_{s,max}$ | η^{ch}_s/η^{dis}_s |
	(MW)	(MW)	(MWh)	(MWh)	(MWh)	(MWh)	(%)
Value	7.5	0.5	18.4	8.7	10	42	92.5
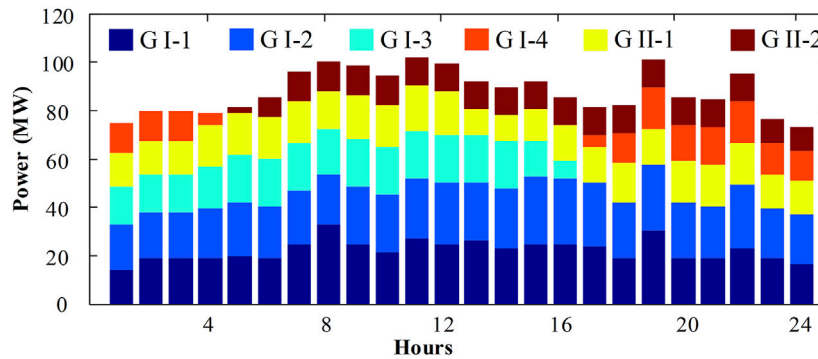
FIGURE 10 | Hourly dispatch results of the generators.

and 91 demands, please see the one-line diagram in **Figure 9** in the previous work (Wang et al., 2008). And the detailed data of the 118-bus system can be found at motor. ece.iit.edu/data/SCUC_118. For simplicity, we also use the same three zones in **Figure 9** (Wang et al., 2008), and assume each zone has the same requirements of decision-making independence and information privacy. The other parameters are the same as those in the small-scale cases. Then the computation time, in this case, is about 1957 s of paralleled CPU time and the objective value has a 0.43% gap with the centralized solution method. This further demonstrates the effectiveness of the proposed method.

Dispatching Results

The hourly commitment and dispatch results are given in **Figure 8**. And the tie-line flow schedules are given in

Figure 9, where a positive power refers to tie-line flow withdrawing from microgrid I and injecting into microgrid II.

The scheduled tie-line flow profiles are similar to the system load profiles. At off-peak hours (14–18 and 20–21) when load demand in microgrid I is low, the power components of the cheapest generator in microgrid I are exported to microgrid II, resulting in negative tie-line flows. Otherwise, at on-peak hours, the local DGs can hardly supply all the loads in microgrid II, it is necessary to import energy from microgrid I to microgrid II, and accordingly, the tie-line schedules are positive at these hours. The results reveal that the coordinated tie-line flows adapt to the load demand in individual microgrids for enhancing the overall economic and steady performances. By comparison, if the two microgrids have no power exchange, then the target value of the robust scheduling is obviously 3.5% higher than that in the
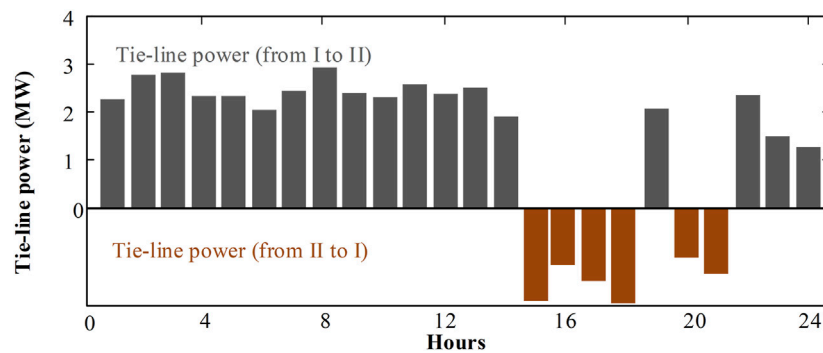
FIGURE 11 | Profiles of the hourly tie-line power components.

networked cases. Essentially, the coordination encourages the economic power flows from the microgrids with lower location marginal price to the microgrids with higher location marginal price. In addition, different microgrids can share their regulatory capabilities to hedge against RDG uncertainty.

Furthermore, to consider future power system with large-scale energy storage, e.g., pumped storage units and megawatt-class batteries, a new scenario in which an energy storage (see **Table 4**) is installed to bus II-5 is introduced. **Figure 10** and **Figure 11** show the dispatching results and the tie-line flow schedules with the additional energy storage. They reveal the influence of energy storage on the scheduling of the networked microgrids. In the new scenario, the total cost is reduced to $ 46,405, about 98.5% of the original one. It illustrates the effectiveness of energy storage in accommodating the volatile DRGs. And it also shows the proposed method can effectively coordinate the scheduling in the new cases with more privacy information, e.g., the parameters of the storage are only known by the microgrid II. However, it is noteworthy that the system obtains an additional $ 715 by introducing a 50 MWh energy storage. The income can hardly cover the investment, especially if costly battery storage is employed. This is an important issue but beyond the scope of this paper.

CONCLUSION

This paper studies the joint scheduling strategy for networked microgrids with high penetration distributed renewable generations. It employs some decomposition

techniques like Augmented Lagrangian, ADMM and CC&G to solve the proposed problem. The developed method can find sub-optimal solutions in a decentralized manner, protecting the decision independence and information privacy of individual microgrids. Case studies demonstrate that the proposed method achieves speed convergence, and the joint scheduling brings obvious economic benefits to the operation of networked microgrids. Future work will consider more demand responses in the dispatching issues of networked microgrids, and more research can be done to improve the computational efficiency of solution method.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Conceptualization, WS and YT; methodology, YZ; software, WS; validation, HZ, QF, and YT; formal analysis, ML; investigation, WS; resources, YZ; data curation, WS; writing—original draft preparation, WS; writing—review and editing, YT; visualization, YS and YZ; supervision, WS; project administration, YT; All authors have read and agreed to the published version of the manuscript.

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