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Decentralized Economic Dispatching of Multi-Micro Grid Considering Wind Power and Photovoltaic Output Uncertainty

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ABSTRACT In this paper, the decentralized economic scheduling problem of multi-micro grid is studied on the basis of considering the uncertainty of wind power and photovoltaic output. Firstly, in order to meet the independent and autonomous requirements of decentralized scheduling, the decoupling method of public connection points, which is more suitable for the multi-micro grid structure, is adopted to partition the multi-micro grid regions. Then, considering the uncertainty of wind-wind output, a decentralized economic dispatching model of multi-micro grid with robust optimization participation is proposed to minimize the economic cost. Finally, the improved Alternating direction method of multipliers is used to solve the decentralized economic scheduling problem of multi-micro grid. The feasibility and superiority of the improved algorithm are verified by simulation test and comparative analysis. The decentralized autonomy of multi-micro grid scheduling can be realized, and the random uncertainty of landscape can be effectively dealt with.

INDEX TERMS Alternating direction method of multipliers (ADMM), decentralized economic scheduling, multi-micro grid, wind power generation.

I. INTRODUCTION

In recent years, the emergence of microgrid provides an effective technical means for the comprehensive utilization of renewable energy [1]. Compared with a single microgrid, though, the structure of a multi-microgrid system is more complex. However, its operation mode is more flexible and the scheduling of electric energy is more reasonable [2]. However, the strong stochastic uncertainty of wind power brings challenges to the economic scheduling problem of multi-micro grid. In addition, the decentralized optimal power flow solution and economic dispatching method has the advantages of high reliability, strong robustness, sharing the computing and communication burden, etc., and is an ideal way for the optimization dispatching of smart grid in the future [3].

In recent years, as a kind of comprehensive integrated low-voltage and medium-voltage power distribution system including renewable energy and other distributed power sources, microgrid has received extensive attention [4]. Therefore, it is of great significance to study the economic scheduling problem of microgrid [5]. At present, the solving algorithm of multi-micro grid scheduling model is mainly centralized optimization method [6]. Common optimization methods include linear programming method [7], dynamic programming method [8], particle swarm optimization algorithm [9], genetic algorithm [10], etc. Literature [11] proposed a microgrid scheduling method based on evolutionary game. Literature [12] adopts the time-varying acceleration coefficient particle swarm optimization (TVAC-PSO) algorithm to study the day-ahead scheduling problem of microgrid. Literature [13] proposed mixed integer linear programming and particle swarm optimization (MILP-PSO) algorithm to study the scheduling of isolated microgrids. However, centralized optimization scheduling of microgrid has disadvantages such as large difference in power supply operation characteristics, difficulty in meeting the network communication requirements of centralized control, and insufficient protection of dispatcher privacy data [14].

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Therefore, the optimal scheduling mode of multi-micro grid is gradually changing from centralized to decentralized [15].

At present, the commonly used methods to deal with output uncertainty mainly include stochastic programming method [16], multi-scenarios method [17] and robust optimization method [18]. In the stochastic programming method, the probability information of wind power output is used for modeling, which can ensure that constraints are satisfied with certain confidence probability. Literature [19] used mixed probabilistic uncertainty set to model the uncertainty of renewable energy according to the output probability within the scope of long-term planning. Scenario method represents the uncertain output of wind power with a limited number of discrete scenarios and corresponds to different scenarios' occurrence probabilities. Literature [20] adopts the improved limit scenario method to establish a multi-source coordinated optimization model for peak regulation of power system with wind power access. Robust optimization method is an uncertain decision-making method based on interval disturbance information. Literature [21] applies the robust optimization method to the economic dispatching problem of electrical energy system, and establishes a two-stage dispatching model with gas turbine and power-to-gas device as coupling components. Literature [22] proposed a market-oriented wind power dispatching strategy based on the adaptive planning method. Literature [23] compensated for the fluctuations of wind power generation and the prediction errors of participating in the power market by adopting a battery energy storage system with short-term operating standards to deal with the prediction error effect. Literature [24] studied the interval scheduling method considering the dynamic cost of wind power based on interval planning method. Although the uncertainties of renewable energy output were taken into account in the system dispatching operation, the above studies were all carried out under the centralized dispatching framework.

There are few researches on decentralized optimal scheduling of micro grid. Literature [25] combines the characteristics of centralized control and decentralized control, and proposes a hierarchical control architecture of DC microgrid. Literature [26] proposes an optimal scheduling model and solution method based on objective cascading analysis theory in view of the decentralized autonomous characteristics of active distribution systems with multiple micro-grids. Literature [27] proposes a new agent-based model to solve the Distributed Constraint Optimal Scheduling (DCOP) problem in microgrids. Alternating Direction Method of Multipliers (ADMM), as an important Method in the field of distributed optimization, is a distributed optimization algorithm based on non-traditional gradient. Compared with general subgradient methods, ADMM has an advantage in that its convergence speed is greatly improved [28]. The core of ADMM is to decompose a complex problem into several subproblems, then carry out alternating iterations on several groups of different variables and update the corresponding dual variables, and finally achieve convergence [29]. As a decentralized method for solving optimization problems, ADMM has good convergence and strong robustness, and has attracted more and more attention in recent years [30]. Literature [31] proposed a distributed optimization framework based on ADMM to solve the problem of optimal size of multiple schemes in power systems. Literature [32] adopts synchronous ADMM to optimize the optimal power flow problem of interconnected grid system with different dispatch centers. Literature [33] proposes a completely decentralized ADMM to solve the reactive power optimization problem of active distribution network. However, the deterministic optimization strategy is adopted in the above related studies of decentralized dispatching, ignoring the influence of the uncertainty of renewable energy output on the dispatching in micro-grid.

In this paper, the decentralized optimal scheduling problem of multi-micro grid is studied on the basis of considering the uncertainty of wind power and photovoltaic output. In this paper, a decentralized economic scheduling model is established to minimize the economic cost of multi-micro grid. Then, the uncertainty problem is dealt with by the robust optimization method. Finally, the improved ADMM is used to carry out the alternating iterative parallel computation between adjacent microgrids, and the decentralized scheduling of multiple microgrids is realized.

II. DECENTRALIZED ECONOMIC SCHEDULING MODELING OF MULTI-MICRO GRID

A. ECONOMIC DISPATCHING MODEL OF MICROGRID

The micro-grid system studied in this paper mainly includes distributed power supply such as photovoltaic power generation system, wind power generation system, emergency diesel generator and energy storage system. The structure of the micro-grid system is shown in Fig. 1. Among them, the photovoltaic power generation system is affected by temperature, light intensity and other factors; Wind power generation system is affected by wind speed, weather and other factors, there are output uncertainties. The output of the diesel unit is stable and controllable, which can be used as the backup of the micro grid system, and also ensure the safe and stable operation of the micro grid. In the energy storage system, the storage battery energy storage system is only considered in this paper, but not the heat storage. For the conventional

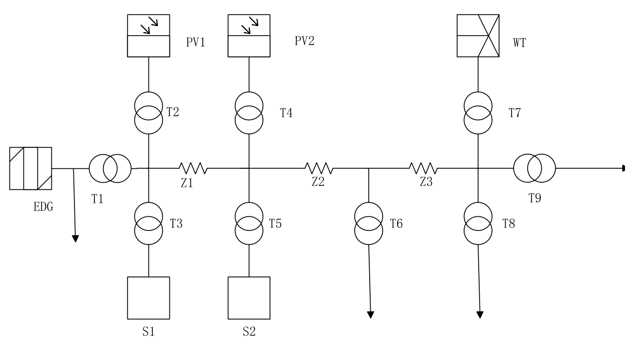

FIGURE 1. Wiring diagram of an actual microgrid.

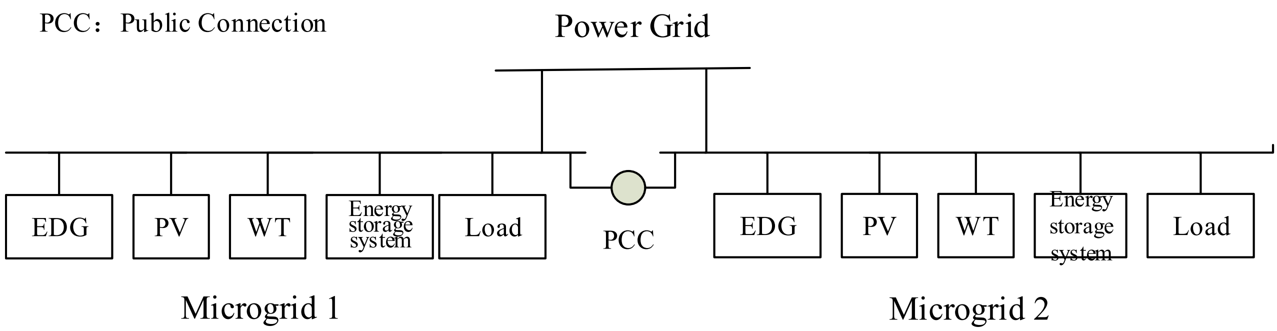

FIGURE 2. Wiring diagram of multi-micro grid.

micro grid as shown in Fig. 1, the economic scheduling model of micro grid is constructed with the goal of minimizing economic cost, as shown below:

$$\min \ F = F_1 + F_2 + F_3 + F_4 \tag{1}$$

In the formula: F_1 is the operating cost of diesel unit; F_2 is the cost of abandoning photovoltaic; F_3 is the cost of abandoning wind power; F_4 is energy storage cost.

$$F_1 = \sum_{g=1}^{G} a_g P_g^2 + b_g P_g + c_g \tag{2}$$

In the formula: P_g is the active power output of the g diesel unit, a_g b_g are the secondary and primary terms of the cost of the g diesel unit, G is the total number of diesel units, c_g is a constant term.

$$F_2 = \sum_{s=1}^{S} (\overline{P}_s - P_s) C_s \tag{3}$$

In the formula: P_s is the output of the s-th photovoltaic power station, $\overline{P}_s$ is the predicted output, C_s is the cost of light abandonment, S is the number of photovoltaic power stations.

$$F_3 = \sum_{w=1}^{W} (\overline{P}_w - P_w) C_w \tag{4}$$

In the formula: P_w is the output of the w-th typhoon power station, $\overline{P}_w$ is the predicted output, C_w is the unit wind abandonment cost, W is the number of wind farms.

$$F_4 = \sum_{b=1}^{B} C_b P_b \tag{5}$$

In the formula: P_b is the active power output of the b-th energy storage device, C_w is the operating cost of the unit power stored/emitted by the energy storage device, B is the total number of energy storage devices.

B. MULTI-MICRO GRID DECENTRALIZED SCHEDULING MODEL

The decentralized computing method of multi-micro grid does not require a control center, and the PCC (Public Connection) among each micro grid can undertake information exchange and computing tasks. In this way, the delay of calculation is avoided and the data privacy between the micro networks is guaranteed.

Before constructing the decentralized economic scheduling model, the system should be partitioned first. At present, the two common partitioning methods are divided according to "region" or "joint node" division. In order to adapt to the structural characteristics of the multi-micro grid system, the partitioning method of single node decoupling is chosen in this paper. Each node is considered as an independent sub-problem for optimization calculation. This partitioning method only requires four variables, namely the real part, the imaginary part and the corresponding multiplier of the voltage interacting with the adjacent nodes. Compared with the centralized algorithm, it has obvious advantages over the mass data transmission and operation. To realize the decentralized scheduling of multi-micro grid as shown in Fig. 2, the first step is to partition the region. The voltage phase Angle of the PCC is the node coupling variable. By copying node information, as shown in Fig. 3, node decoupling can be realized.

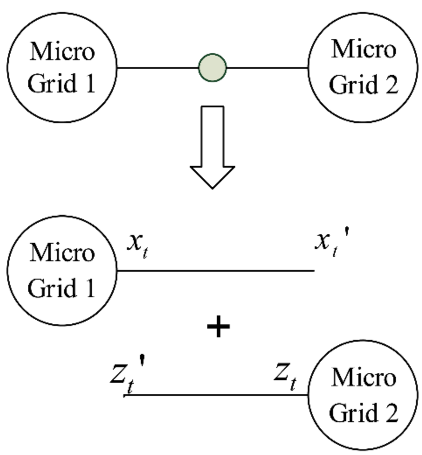

FIGURE 3. Microgrid node partition.

According to the partitioning method of decoupling PCC, the decentralized scheduling model of multi-micro grid is constructed as follows:

$$\begin{cases} \min \sum_{r=1}^{R} F_r(X_r) \\ s.t.\ g_r(X_r) = 0 \\ h_{r\min} \le h_r(X_r) \le h_{r\max} \\ g_b(x_1, \ldots\ldots, x_r) = 0 \end{cases} \tag{6}$$

In the formula: R is the total number of microgrids.

C. THE CONSTRAINT

1) THE UPPER AND LOWER LIMITS ON THE ACTIVE POWER OUTPUT OF THE POWER SUPPLY

The output of diesel units, photovoltaic power stations, wind power stations and accumulators in the microgrid is between the upper and lower limits at all times:

$$P_{g\min} \le P_g \le P_{g\max} \tag{7}$$

In the formula: $P_{g\min}$ and $P_{g\max}$ are the lower limit and upper limit of the output of the g diesel unit respectively.

The active power output constraint of photovoltaic power station is:

$$0 \le P_s \le \overline{P}_s \tag{8}$$

The active power output constraint of wind power station is:

$$0 \le P_w \le \overline{P}_w \tag{9}$$

2) ENERGY STORAGE CONSTRAINT

$$SOC_{b\min} \le SOC_{b,t} \le SOC_{b\max} \tag{10}$$

In the formula: $SOC_{b,t}$ is the charge of battery b at time t; $SOC_{b\min}$ and $SOC_{b\max}$ are the lower limit and upper limit of battery b charge.

$$SOC_{b\,min} = \rho_{min} SOC_b \tag{11}$$

$$SOC_{b\,max} = \rho_{max} SOC_b \tag{12}$$

In this formula, ρ_{min} and ρ_{max} are the minimum and maximum SOC of the battery respectively.

3) STANDBY CONSTRAINT OF DIESEL UNIT

$$\begin{aligned} P_g + R_g^U &\le u_g P_{g\max} \\ P_g - R_g^D &\ge u_g P_{g\min} \end{aligned} \tag{13}$$

In the formula: R_g^U and R_g^D are the positive and negative reserve regulation quantities of the diesel unit respectively, u_g refers to the start-stop state of the diesel unit.

4) BOUNDARY COUPLING CONSTRAINT

In addition to the equality constraints and inequality constraints that need to be satisfied within a single micro grid, it is also necessary to make the phase angles of the PCC between adjacent micro grids equal.

$$\theta_1 = \theta_2 \tag{14}$$

θ_1 and θ_2 are respectively the voltage phase angles of the two microgrids at the common coupling point.

III. MULTI-MICRO GRID DECENTRALIZED SCHEDULING MODEL CONSIDERING WIND AND PHOTOVOLTAIC OUTPUT UNCERTAINTY

A. WIND AND PHOTOVOLTAIC OUTPUT UNCERTAINTY PROCESSING

Robust optimization is an improvement of stochastic optimization method. A new model is established to deal with the uncertainty problem by setting the uncertain parameters as a bounded and closed uncertain set U. Compared with other common algorithms for dealing with uncertain problems, it has unique advantages. The robust optimization algorithm only needs to determine the set of the range of uncertain parameters, which requires less data and is easy to calculate. Robust optimization can reduce the sensitivity of the result to disturbance and ensure good robustness.

Then the model with the uncertainty robust optimization is as follows:

$$\begin{cases} min_{x\in R^n} F(x,\partial), & x \in R^n,\ \partial \in U \\ s.t.\ h(x,\partial) \le 0, & \forall \partial \in U,\ (i = 1, \ldots\ldots, m) \end{cases} \tag{15}$$

Or:

$$\begin{cases} minsup F(x,\partial), & x \in R^n,\ \partial \in U \\ s.t.\ sup(x,\partial) \le 0, & \forall \partial \in U,\ (i = 1, \ldots\ldots, m) \end{cases} \tag{16}$$

Compared with other stochastic optimizations, the robust optimization based on uncertain sets is more convenient to calculate. The result obtained by using robust optimization to deal with uncertain problems is the optimal solution under all scenarios including the worst scenario, which has strong anti-interference and conservatism, so it is also called strong robust optimization.

B. DECENTRALIZED SCHEDULING MODEL OF MULTI-MICRO GRID CONSIDREING OUTPUT UNCERTAINTY

Considering the random uncertainty of wind power and photovoltaic power generation, the output formula is as follows:

$$P_{WT} = \bar{P}_{WT} + \tilde{P}_{WT} \tag{17}$$

$$s.t.\ \tilde{P}_{WTmin} \le \tilde{P}_{WT} \le \tilde{P}_{WTmax} \tag{18}$$

$$P_{PV} = \bar{P}_{PV} + \tilde{P}_{PV} \tag{19}$$

$$s.t.\ \tilde{P}_{PVmin} \le \tilde{P}_{PV} \le \tilde{P}_{PVmax} \tag{20}$$

In the formula: $\bar{P}_{WT}$, $\bar{P}_{PV}$ are respectively wind power output and photovoltaic output in the microgrid; $\tilde{P}_{WT}$, $\tilde{P}_{PV}$ are respectively the output errors of wind power and photovoltaic power in the microgrid; $\tilde{P}_{WTmax}$, $\tilde{P}_{PVmax}$ are the upper limits of the error of wind power output and photovoltaic power output of the microgrid; $\tilde{P}_{WTmin}$, $\tilde{P}_{PVmin}$ are the lower limits of the error of wind power output and photovoltaic power output of the microgrid.

The objective function adds the penalty cost of the uncertainty of renewable energy forecast to the cost, as follows:

$$min\ F = F_1 + F_2 + F_3 + F_4 + \mu\left(\tilde{P}_{WT} + \tilde{P}_{PV}\right) \quad (21)$$

In the formula: μ is the uncertainty penalty coefficient of renewable energy output forecast; C_{wt} and C_{pv} are the economic cost of abandoning wind energy and photovoltaic energy.

C. CONSTRUCTION OF UNCERTAIN SCENARIO SETS

The wind farm reports the forecast value of wind power output from 0 to 24 o 'clock the next day to the dispatching center every day. In this paper, the scheduling cycle T is divided into 24 periods, and the predicted value of wind power output is regarded as a certain quantity to construct the uncertainty set of wind power. Therefore, the actual output of wind power can be expressed as:

$$P^W_{k,t} \in [\bar{P}^W_{k,t} - \Gamma_W \hat{P}^W_{k,t}, \bar{P}^W_{k,t} + \Gamma_W \hat{P}^W_{k,t}], \quad \Gamma_W \in [0, 1] \quad (22)$$

In the formula: $\hat{P}^W_{k,t}$ is the prediction error of wind power output at time t; Γ_W is the robustness coefficient of wind power. The fluctuation range of wind power output can be controlled by adjusting the value of Γ_W within its interval.

Similarly, the actual output of photovoltaic power generation can be expressed as:

$$P^P_{k,t} \in [\bar{P}^P_{k,t} - \Gamma_P \hat{P}^P_{k,t}, \bar{P}^P_{k,t} + \Gamma_W \hat{P}^P_{k,t}], \quad \Gamma_P \in [0, 1] \quad (23)$$

In the formula: $\hat{P}^P_{k,t}$ is the prediction error of photovoltaic power output at time t; Γ_P is the robustness coefficient of photovoltaic power. The fluctuation range of wind power output can be controlled by adjusting the value of Γ_P within its interval.

The multi-micro grid decentralized scheduling model constructed above, which takes into account the uncertainty of wind power and photovoltaic output, is an interval model and cannot be solved by the model. At present, effective objective function is one of the commonly used methods to solve robust optimization problems. First, the original objective function is written into the form of effective objective function, and then the effective objective function is solved. Some sampling methods are usually used to approximate the effective objective function, such as Monte Car-lo Integra and Latin Hypercube Sampling (LHS), etc. Comparatively speaking, the LHS method makes the sampling results more uniform, which is in line with the actual situation of this paper. In this paper, the LHS method is used for sampling approximate calculation.

IV. IMPROVED ALTERNATE DIRECTION METHOD OF MULTIPLIERS

A. THE ORIGINAL ALTERNATING DIRECTION METHOD OF MULTIPLIERS

ADMM is mainly used to solve optimization problems with separable variables. ADMM originally came from the solution of the dual ascent problem. When the objective function of the convex optimization problem is separable, the dual decomposition is needed to construct the Lagrange equation. But the Lagrange multiplier method cannot do dual decomposition. Therefore, the ADMM is obtained by improving the Lagrange multiplier method.

Two - variable standard ADMM forms are as follows:

$$\begin{cases} \min f(x) + g(z) \\ s.t.\ Ax + Bz - c = 0 \end{cases} \quad (24)$$

f and g are real numeric convex functions; x and z are all optimization vectors, $x \in R^n, z \in R^m$; A, B, c are coupled matrices, $A \in R^{p\times n}, B \in R^{p\times m}, c \in R^p$.

When functions f and g are convex functions on $R^n \to R \cup \{+\infty\}$, the algorithm converges to the optimal solution. In addition, f and g can represent not only the objective function of A single micro grid, but also the equality or inequality constraint of each micro grid. In this case, if the constraint of each subnet does not exceed the limit, $f = 0$, $g = 0$. Otherwise, $f = +\infty, g = +\infty$.

By using the Gosseidel method, Lagrange equation in the following form is constructed, and its iterative equation can be obtained as follows:

$$\begin{aligned} x^{t+1} &= \arg\min L_\rho(x, z^t, y^t) \\ z^{t+1} &= \arg\min L_\rho(x^{t+1}, z, y^t) \\ y^{t+1} &= y^t + \rho(Ax^{t+1} - z^{t+1}) \end{aligned} \quad (25)$$

In this formula, y is expressed as A Lagrange multiplier, ρ is the penalty factor. x and z are the original variables. Alternate iterative optimization updates between original variables are called alternate directions. When f and g are separable objective functions, ADMM algorithm is still able to optimize the solution of the problem.

In the standard ADMM, the optimization iterations between the two areas are carried out alternately in a pre-arranged order. The latest optimization value of the former region is substituted into the latter region for optimization solution. The global iteration variable is updated through the global coordination center after the optimization of all regions is completed successively. The optimization process is shown in Fig. 4.

B. THE IMPROVED ADMM

The asynchronous iteration ADMM can update each sub-variable very fast when solving the optimization problem.

However, the iteration of all sub-variables is carried out in a certain sequence, so the solving time is long and the efficiency is not high. Therefore, in order to realize the synchronous optimization of ADMM, the following Jacobian iterative equation ADMM is obtained:

$$\begin{aligned} x_i^{t+1} &= \arg\min f_i(x_i) + \frac{\rho}{2}\left\| A_i x_i + \sum\nolimits_{j\neq i} A_j x_j^t - c - \frac{y^t}{\rho}\right\|_2^2 \\ y^{t+1} &= y^t - \rho(\sum\nolimits_{i=1}^N A_i x_i^{t+1} - c) \end{aligned} \quad (26)$$

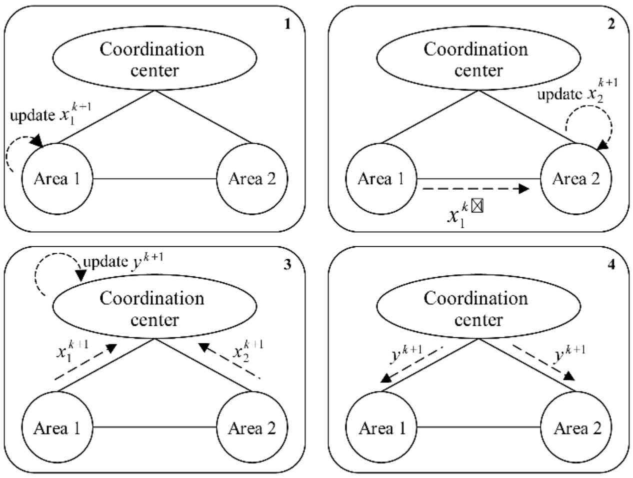

FIGURE 4. Schematic diagram of standard ADMM between two regions.

That is, on the basis of the original algorithm, each sub-variable takes into account the updated value of the last iteration of the adjacent sub-variables related to the existence of its own equality constraints when updating the variables in this iteration. This enables parallel optimization. However, when the sub-variable is optimized in this iteration (t + 1), it can only obtain the updated value of the previous iteration(t) optimization of the adjacent sub-variable. In this way, the information exchange and update between adjacent subproblems are not timely enough, and the calculation time increases.

The identity matrix E is selected for matrix A, and the Lagrange multiplier y^t is the updated value after the optimization of the t iteration in the optimization process. Therefore, this whole term is regarded as a constant in the t + 1 iterative optimization, which can be ignored and can be simplified into the following form:

$$\begin{cases} x^{t+1} = \arg\min(f(x) + \frac{\rho}{2}\left\|x - z^t + \mu^t\right\|^2 \\ z^{t+1} = \arg\min(g(z) + \frac{\rho}{2}\left\|x^{t+1} - z + \mu^t\right\|^2 \\ \mu^{t+1} = \mu^t + (x^{t+1} - z^{t+1}) \end{cases} \tag{27}$$

In this formula:

$$\mu^t = (1/\rho)y^t \tag{28}$$

The mathematical meaning of the variable μ can still be understood as the generalized Lagrange multiplier.

In order to simplify the calculation, the average value of the boundary variable corresponding to the calculation results of the t iteration of the two regions was selected as the fixed value of the t + 1 iteration. It is only used to replace the standard ADMM to select the boundary variable value of the adjacent region in the t + 1 iteration:

$$K_x^t = K_z^t = \frac{x^t + z^t}{2} \tag{29}$$

In this formula, K_x^t and K_z^t are fixed reference values used in the iterative calculation of the t + 1 time of the subproblem with adjacent correlation constrained by equality.

Through the above improvements, the final iteration form of the two-region synchronous ADMM is obtained:

$$\begin{cases} x^{t+1} = \arg\min(f(x) + \frac{\rho}{2}\left\|x - K^t + \mu^t\right\|^2) \\ z^{t+1} = \arg\min(g(z) + \frac{\rho}{2}\left\|K^t - z - \mu^t\right\|^2) \end{cases} \tag{30}$$

In this formula:

$$\begin{cases} \mu^{t+1} = \mu^t + (x^{t+1} - z^{t+1}) \\ K^t = \frac{x^t + z^t}{2} \end{cases} \tag{31}$$

The above is the principle of the improved synchronous iteration ADMM of the two regions. Its basic idea is as follows: each region is divided for independent solution, and variables of the boundary should be exchanged and updated after each solution of each region. Each region can realize parallel computation in each solution process. In addition, the iteration variables of each region are calculated independently, thus eliminating the role of coordination center to achieve fully decentralized control. The optimization process is shown in Fig. 5.

C. MODEL SOLUTION PROCESS

The solving steps of the model are as follows:

1) Based on the scenario method, independently generate the prediction scenario and error scenario values of wind power in each region;
2) Initialize the initial value of each variable and define the original residuals;
3) The $t+1$ iteration of micro-grid 1: the objective function z_t, Lagrange multiplier μ_t in the adjacent micro-grid 2 and the objective function x_t of microgrid 1 to update the x_{t+1} of this region;
4) The $t+1$ iteration of the microgrid 2: the objective function x_t, Lagrange multiplier μ_t of the adjacent microgrid 1 and the objective function z_t of the micro-grid 2 are used to update the z_{t+1} of this region;
5) Lagrange multiplier μ_{t+1} is updated in each microgrid region;
6) Convergence judgment. If the calculation results meet the termination conditions, the iteration is ended. If not convergent, the calculation step is repeated.

V. SIMULATION ANALYSIS OF CALCULATION EXAMPLES

A. INTRODUCTION OF SIMULATION EXAMPLES

The renewable energy equipment in each microgrid includes two photovoltaic power stations and one wind power station. At the same time, it is equipped with a storage battery as an energy storage device and 1-2 emergency diesel generator. In the case that the renewable energy cannot meet the load, the diesel unit will be started to provide support.

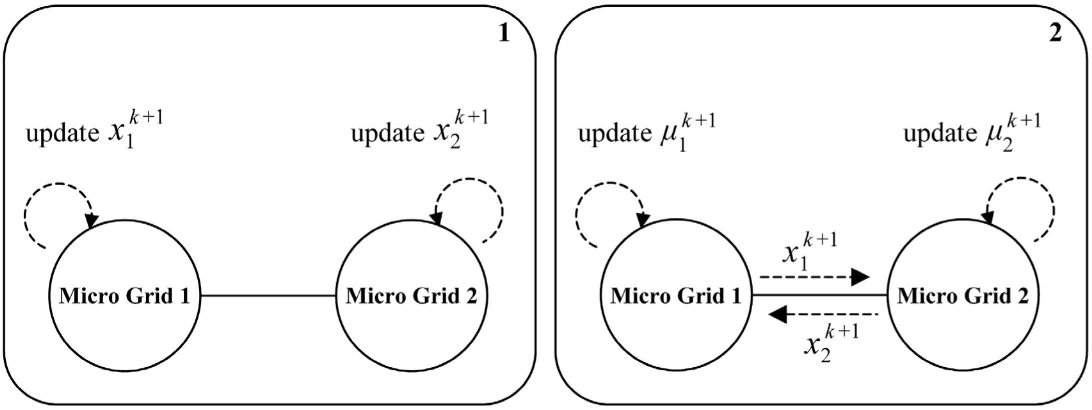

FIGURE 5. Schematic diagram of improved ADMM between two micro grids.

TABLE 1. Micro power supply parameters.

	Diesel engine parameters					Storage battery parameters			
	P_{max}/kW	$U_R/(kW\cdot h)$	$D_R/(kW\cdot h)$	$a/(kW^2\cdot h)$	$b/(kW\cdot h)$		P_{max}/kW	$SOC_{min}/(kW\cdot h)$	$SOC_{max}/(kW\cdot h)$
numerical	600	300	300	0.000463	1.69	Parameters of battery 1	1500	0	500
						Parameters of battery 2	300	0	1300

In this paper, the algorithm is applied to a practical microgrid, and the micropower parameters are shown in Table 1. The charging efficiency of the storage battery is 0.85. In the micro grid, the light abandoning cost of photovoltaic power station is taken as 1 ¥/(kW·h), and the wind abandoning cost of wind power station is taken as 0.61 ¥/(kW·h). The number of periods in day ahead of economic schedule is T = 24, that is, ΔT = 1 h. It is assumed that the predicted error of wind power generation obeys the mathematical expectation is the predicted value of wind power, and the standard deviation is the normal distribution of 30% of the predicted value. On the basis of wind power prediction scenarios, 10 error scenarios are generated independently for wind farms in each region, and the probability of each error scenario is 1/10. The global constant of the decentralized algorithm is 50000, and the convergence criterion is 10^{-6}.

The load curve of the microgrid is shown in Fig. 6. At a low level in the early morning, the load increases during the day and reaches its peak at night. The predicted output curves of photovoltaic and wind power of microgrid are shown in Fig. 7. The predicted photovoltaic output is related to the operating law of the sun, and reaches the peak of photovoltaic output at noon. Wind power forecast output is relatively average at all times.

Fig. 8 is the output curve comparison diagram of each power supply of the micro grid. At noon, the output of photovoltaic power station is the maximum, the diesel engine is shut down, and the battery unit is charged. At this time,

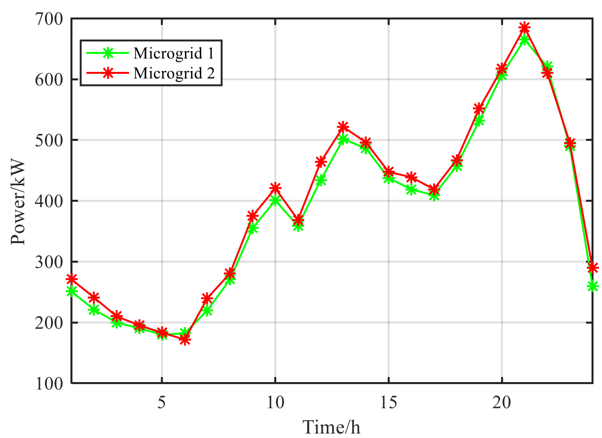

FIGURE 6. Load curve.

the output of photovoltaic and wind power is still greater than the load. Wind abandonment measures are taken because of the higher cost of light abandonment. At night, the load of the microgrid increases. At this time, the output of photovoltaic

B. COMPARISON OF CENTRALIZED ALGORITHM AND IMPROVED ADMM ALGORITHM

Fig. 9 shows the convergence curve of the objective function of decentralized scheduling in microgrid. The curve oscillates at the beginning of the iteration and converges to the optimal

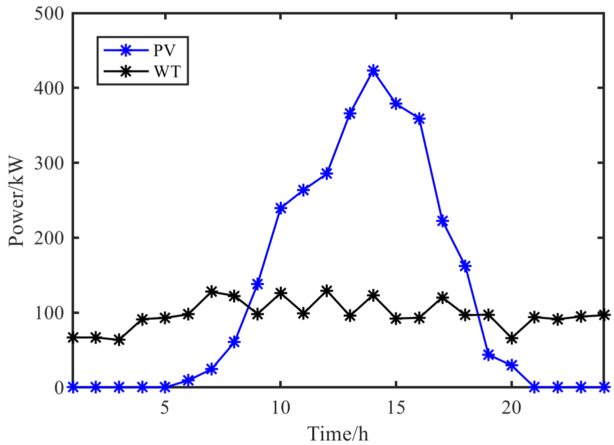

FIGURE 7. Forecast curve of photovoltaic and wind power output.

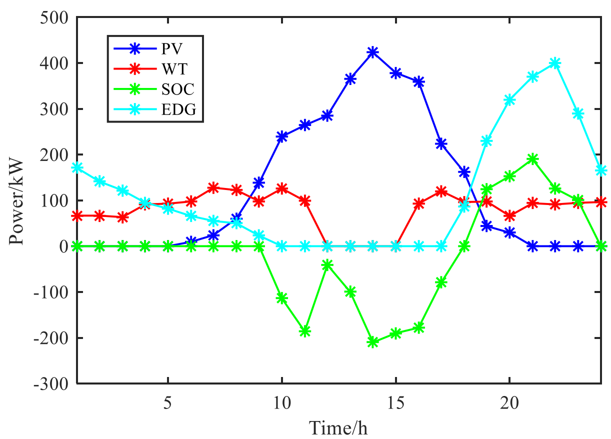

FIGURE 8. Output curve of each power supply.

solution quickly and stably at the end of the iteration. It has strong stability.

In order to reflect the performance of centralized optimization scheduling algorithm, ADMM algorithm and the improved ADMM algorithm proposed in this paper, the same set of data is used to compare the following three schemes.

Scheme A: The centralized optimal scheduling algorithm is used to solve the economic scheduling model of multi-micro grid.

Scheme B: Admm algorithm is used to solve the decentralized economic scheduling model of multi-micro grid.

Scheme C: The improved ADMM algorithm is used to solve the decentralized economic scheduling model of multi-micro grid.

The comparison of the abandoned air volume of the optimal solution between scheme A and scheme C is shown in Figure 10. The time period of wind abandonment measures were all taken around noon (11:00 to 15:00), with an error of only 2.9%.

The same original data is used to solve the multi-micro grid economic scheduling model through three different optimal scheduling algorithms. The simulation results are shown in Table 2. It is obvious that the results of centralized scheduling algorithm and decentralized scheduling algorithm are very close. The total cost error of the final results was only 0.12% and 0.23%. Thus, compared with the centralized scheduling algorithm and the standard ADMM algorithm, the improved ADMM algorithm proposed in this paper can also accurately reflect the optimal scheduling results of the multi-micro grid.

TABLE 2. Performance comparison of centralized and decentralized optimization algorithms.

Algorithm	Cost	Number of iteration	Iteration time
centralized	6579	——	22.3
ADMM	6587	1179	845.4
improved ADMM	6594	1853	707.1

By comparing the relevant data of iteration time and iteration number in Table 2, it can be seen that the centralized optimization algorithm has the shortest iteration time. The standard ADMM method needs to optimize the solution of each region in sequence, and the number of iterations is relatively small, but it needs a coordination center to update the global iteration variable when it is iterated. The improved ADMM method can update the iterative variables within each microgrid region by itself, so there is no need for the control of the coordination center, and the parallel optimization iterative solution of each microgrid region is still completely decentralized. Although the number of iterations of the improved ADMM algorithm is relatively more, the time of optimal scheduling can be shortened by parallel iterative calculation between each microgrid region in the calculation process. In addition, the model in this paper is only a computational task performed on a single computer. When the distributed scheduling method is applied in practice, the power generation plan of each microgrid will be carried out by multiple computers distributed in different geographical locations simultaneously. This practical working mode can make up for the disadvantage of distributed scheduling algorithm in terms of computation speed.

C. ANALYSIS OF SIMULATIONRESULTS CONSIDERING THE UNCERTAINTY OF OUTPUT

Fig. 11 and Fig. 12 respectively show the generated photovoltaic output prediction scenario and wind power output prediction scenario.

In order to show the superiority of multi-micro grid decentralized scheduling model considering the output uncertainty of wind power and photovoltaic in robust environment, the same set of original data is used to compare the following two schemes in this paper.

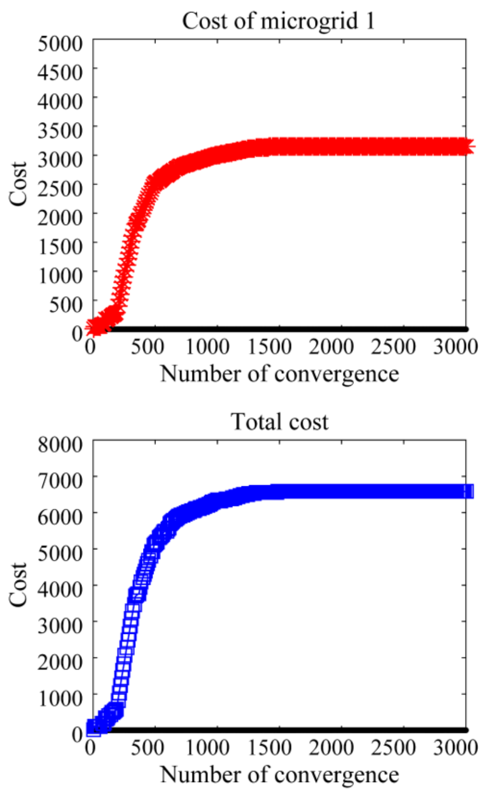

FIGURE 9. Convergence curve of objective function.

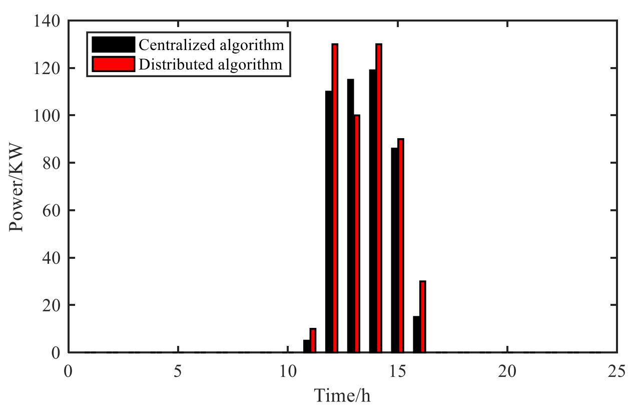

FIGURE 10. Comparison diagram of the abandoned air volume of the two schemes.

Scheme A: The improved ADMM algorithm is used to solve the decentralized economic scheduling model of multi-micro grid without considering the uncertainty.

Scheme B: The improved ADMM algorithm is used to solve the decentralized economic scheduling model of multi-micro grid in a robust environment considering uncertainty.

The power output curves of the optimal solution after considering the uncertainty of wind and photovoltaic output are shown in Fig. 13. For the model without considering uncertainty solved by the improved ADMM algorithm and the multi-micro grid decentralized scheduling model with considering uncertainty in a robust environment, the results are shown in Table 3.

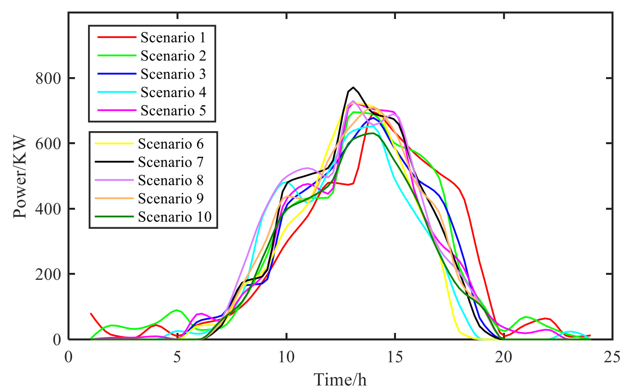

FIGURE 11. Generated photovoltaic power scenarios.

TABLE 3. Simulation results in two scenarios.

Scenario	Cost	Number of iteration	Iteration time
1	6584	1753	718.2
2	6607	2045	971.6

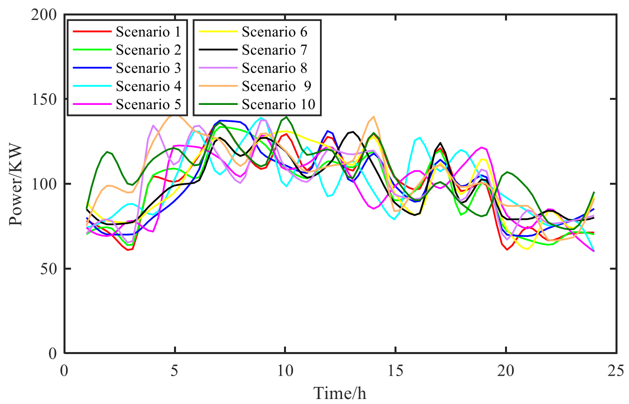

FIGURE 12. Generated wind power scenarios.

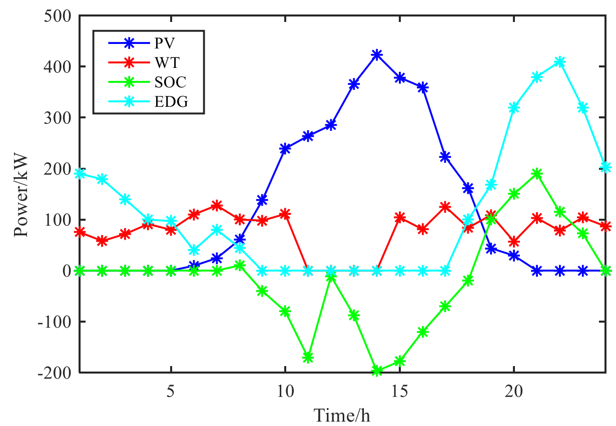

FIGURE 13. The power output curves after considering the uncertainty output.

It can be concluded from Table 3 that the total cost is 3.1% higher when uncertainty is considered. This indicates that when the influence of uncertainty on generation planning and output is considered in the model, the total operating cost of the system is slightly greater than the result of the model without uncertainty. The total cost is increased because the initial unit output plan is changed to take into account the error scenario. By adjusting the start-stop state of the diesel engine set, all the scenes in the error scene set can meet the requirements as far as possible. And with the increase of the prediction error range, it will inevitably increase the economic cost. Therefore, when solving the decentralized dispatching model of multi-micro grid considering uncertainty through robust optimization, decision makers should reasonably plan the renewable energy output according to the local conditions.

In addition, the solution time when considering uncertainty is longer than that of the decentralized multi-micro grid scheduling model without considering uncertainty. This is because the calculation of error scenarios is included in the calculation, resulting in a significant increase in the calculation time. And the more error scenarios, the higher the computational complexity will be.

VI. CONCLUSION

Based on the uncertainty of wind power and photovoltaic output, a decentralized optimal scheduling model of multi-micro grid is established in this paper. The improved ADMM algorithm was used to solve the problem, and the following conclusions are drawn:

1) Decentralized scheduling model has high stability. It can reliably converge to the global optimal solution consistent with the centralized optimization, which verifies the feasibility of the model.
2) Considering the robust optimization method to deal with the uncertain problems, it increases the economic cost to some extent. However, it can better deal with the random uncertainty problems faced by multi-micro grid scheduling in real life.
3) The improved ADMM can realize the parallel calculation among the micro grids, which can shorten the iteration time compared with the traditional ADMM method. Moreover, there is less information exchanged among the micro networks, which realizes the decentralized autonomy of the micro network scheduling. This proves the superiority of the model in this paper.

REFERENCES

[1] M. Wu, X. Xiong, Y. Ji, B. Ding, and Y. Zhang, "Overview on multi-microgrid technologies," *Energy Storage Sci. Technol.*, vol. 8, no. 4, pp. 621–628, Jul. 2019.

[2] Z. Xu, P. Yang, Z. Zhao, and C. Wang, "Analysis on the development of multi-microgrid in China," *Autom. Electr. Power Syst.*, vol. 40, no. 17, pp. 224–231, Sep. 2016.

[3] W. Lu, M. Liu, S. Lin, and H. Feng, "Decentralized solution for optimal power flow of multi-area interconnected power systems based on distributed interior point method," *Proc. CSEE*, vol. 36, no. 24, pp. 6828–6837, Dec. 2016.

[4] K. Moharm, "State of the art in big data applications in microgrid: A review," *Adv. Eng. Informat.*, vol. 42, Oct. 2019, Art. no. 100945.

[5] J. Liu, C. Zhou, H. Gao, Y. Guo, and Y. Zhu, "A day-ahead economic dispatch optimization model of integrated electricity-natural gas system considering hydrogen-gas energy storage system in microgrid," *Power Syst. Technol.*, vol. 42, no. 1, pp. 170–179, Jan. 2018.

[6] T. Ji, D. Hong, J. Zheng, Q. Wu, and X. Yang, "Wind power forecast with error feedback and its economic benefit in power system dispatch," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 21, pp. 5730–5738, Nov. 2018.

[7] A. Hoke, A. Brissette, S. Chandler, A. Pratt, and D. Maksimović, "Look-ahead economic dispatch of microgrids with energy storage, using linear programming," in *Proc. 1st IEEE Conf. Technol. Sustain. (SusTech)*, Portland, OR, USA, Aug. 2013, pp. 154–161.

[8] J. Zhao and M.-X. Wang, "Dynamic economic dispatch of microgrid based on dynamic programming," *J. Northeast Dianli Univ.*, vol. 36, no. 2, pp. 19–25, Apr. 2016.

[9] G. Yuan and W. Yang, "Study on optimization of economic dispatching of electric power system based on hybrid intelligent algorithms (PSO and AFSA)," *Energy*, vol. 183, pp. 926–935, Sep. 2019.

[10] D. Yang, Y. Liu, X. Shen, L. Xu, Y. Liu, and Q. Chen, "Cooperative dispatch model of multi-microgrid based on chance constrained programming," *Electr. Meas. Instrum.*, vol. 56, no. 18, pp. 47–54, Sep. 2019.

[11] Y. Xu and X. Yan, "A microgrid scheduling method based on evolutionary game," *J. Phys., Conf. Ser.*, vol. 1549, Jun. 2020, Art. no. 052074.

[12] M. Hemmati, B. Mohammadi-Ivatloo, M. Abapour, and A. Anvari-Moghaddam, "Day-ahead profit-based reconfigurable microgrid scheduling considering uncertain renewable generation and load demand in the presence of energy storage," *J. Energy Storage*, vol. 28, Apr. 2020, Art. no. 101161.

[13] R.-K. Kim, M. B. Glick, K. R. Olson, and Y.-S. Kim, "MILP-PSO combined optimization algorithm for an islanded microgrid scheduling with detailed battery ESS efficiency model and policy considerations," *Energies*, vol. 13, no. 8, p. 1898, Apr. 2020.
[14] X. Zhou, Z. Yu, Q. Ai, and S. Zeng, "Review of optimal dispatch strategy of microgrid with CCHP system," *Electr. Power Autom. Equip.*, vol. 37, no. 6, pp. 26–33, Jun. 2017.
[15] C. Ouyang, M. Liu, S. Lin, and H. Feng, "Decentralized dynamic economic dispatch algorithm of microgrids using synchronous alternating direction method of multipliers," *Trans. China Electrotech. Soc.*, vol. 32, no. 5, pp. 134–142, Mar. 2017.
[16] M. Zhang, Z. Hu, X. Wang, M. Hu, M. Hu, and Z. Zhang, "Two-stage stochastic programming scheduling model based on dynamic scenario sets and demand response," *Autom. Electr. Power Syst.*, vol. 41, no. 11, pp. 68–76, Apr. 2017.
[17] H. Zhang and W. Li, "A wind power scenario prediction method with prediction interval boundary as constraints," *Power Syst. Clean Energy*, vol. 34, no. 12, pp. 48–52 and 58, Dec. 2018.
[18] S. He *et al.*, "Summary of theoretical analysis and application of split bludon optimization method in power system," *Autom. Electr. Power Syst.*, vol. 44, no. 14, pp. 179–191, Apr. 2020.
[19] Z. Liang, H. Chen, S. Chen, Z. Lin, and C. Kang, "Probability-driven transmission expansion planning with high-penetration renewable power generation: A case study in Northwestern China," *Appl. Energy*, vol. 255, Dec. 2019, Art. no. 113610.
[20] H. Hu, H. Wei, and Z. Li, "Coordinated optimization model considering nuclear power participating in peak load regulation of power system with wind power," *Electr. Power Autom. Equip.*, vol. 40, no. 5, pp. 31–37, May 2020.
[21] Y. Shui, J. Liu, H. Gao, G. Qiu, W. Xu, and J. Gou, "Two-stage distributed robust cooperative dispatch for integrated electricity and natural gas energy systems considering uncertainty of wind power," *Autom. Electr. Power Syst.*, vol. 42, no. 13, pp. 43–50, Jul. 2018.
[22] M. Khalid, R. P. Aguilera, A. V. Savkin, and V. G. Agelidis, "A market-oriented wind power dispatch strategy using adaptive price thresholds and battery energy storage," *Wind Energy*, vol. 21, no. 4, pp. 242–254, Apr. 2018.
[23] M. Gholami, S. H. Fathi, J. Milimonfared, Z. Chen, and F. Deng, "A new strategy based on hybrid battery–wind power system for wind power dispatching," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 1, pp. 160–169, Jan. 2018.
[24] Q. Ma, X. Sun, Y. Chen, D. Yu, and Q. Xu, "Power system interval economic dispatch incorporating dynamic cost of wind power," *Electr. Meas. Instrum.*, vol. 53, no. 10, pp. 16–21,38, May 2016.
[25] W. Li, Y. Gu, Y. Wang, X. Xiang, and X. He, "Control architecture and hierarchy division for renewable energy DC microgrids," *Autom. Electr. Power Syst.*, vol. 39, no. 9, pp. 156–163, May 2015.
[26] M. Xie, X. Ji, S. Ke, and M. Liu, "Autonomous optimized economic dispatch of active distribution power system with multi-microgrids based on analytical target cascading theory," *Proc. CSEE*, vol. 37, no. 17, pp. 4911–4921, Sep. 2017.
[27] F. Lezama, J. Palominos, A. Y. Rodríguez-González, A. Farinelli, and E. M. de Cote, "Agent-based microgrid scheduling: An ICT perspective," *Mobile Netw. Appl.*, vol. 24, no. 5, pp. 1682–1698, Oct. 2019.
[28] Y.-G. Hong and Y.-Q. Zhang, "Distributed optimization: Algorithm design and convergence analysis," *Control Theory Appl.*, vol. 31, no. 7, pp. 850–857, Jul. 2014.
[29] L. Dong, C. Gong, N. Chen, and T. Pu, "Multi-objective distributed optimal dispatch of active distribution network based on alternating direction method of multipliers," *Electr. Power Construct.*, vol. 38, no. 4, pp. 41–49, Apr. 2017.
[30] N. A. Korgin and V. O. Korepanov, "Experimental gaming analysis of ADMM dynamic distributed optimization algorithm," *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 574–579, Jan. 2016.
[31] J. Chen, Z. Lin, J. Ren, W. Zhang, Y. Zhou, and Y. Zhang, "Distributed multi-scenario optimal sizing of integrated electricity and gas system based on ADMM," *Int. J. Electr. Power Energy Syst.*, vol. 117, May 2020, Art. no. 105675.
[32] Z. Liang, S. Lin, and M. Liu, "Distributed optimal power flow of AC/DC interconnected power grid using synchronous ADMM," *IOP Conf. Ser., Mater. Sci. Eng.*, vol. 199, May 2017, Art. no. 012013.
[33] W. Zheng, W. Wu, B. Zhang, H. Sun, and Y. Liu, "A fully distributed reactive power optimization and control method for active distribution networks," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1021–1033, Mar. 2016.

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