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Cooperative Game-Based Collaborative Optimal Regulation-Assisted Digital Twins for Wide-Area Distributed Energy

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Abstract: With the wide use of renewable energy sources and the requirement for energy storage technology, the field of power systems is facing the need for further technological innovation. This paper proposes a wide-area distributed energy model based on digital twins. This model was constructed to more fully optimize the coordination of wide-area distributed energy in order to rationally deploy and utilize new energy units. Moreover, the minimization of the power deviation between the dispatch command and the actual power regulation output was also taken into account. In contrast to previous dispatch research, the cooperative game co-optimization algorithm was applied to this model, enabling a distributed approach that can quickly obtain a high-quality power command scheduling scheme. Finally, the simulation and comparison experiments using this algorithm with the wide-area distributed energy (WDE) model showed that it had the advantages of significantly reducing the tracking error, average error, and total error and effectively improving the tracking accuracy. The proposed method can help reduce total power deviations by about 61.1%, 55.7%, 53.1%, and 74.8%.

Keywords: wide-area distributed energy; cooperative game; collaborative optimal control; digital twins

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1. Introduction

From an energy standpoint, a whole new era in energy, marked by the wide-scale exploration and deployment of new energy resources, is flourishing around the world [1]. In recent years, the field of power systems has faced major reforms as traditional energy sources have become gradually depleted and people have become increasingly aware of environmental protection.

The new energy sources are renewable and they are available for human exploitation. New energy is embodied in the unconventional energy sources mentioned above. Fossil fuels, such as coal, oil, and natural gas, are conventional energy sources. Recently, the level of technology and equipment for renewable energy sources has significantly improved, and the cost of power generation from renewable energy sources has continuously declined. Additionally, the rise of the energy revolution and the supply-side reform of the power market have spurred the rapid development of renewable energy sources, such as solar energy, wind energy, and biomass. This development is further transforming the energy structure, reducing reliance on conventional fossil fuels. Smart grid technology and energy storage technology can make large-scale distributed energy systems a win-win situation for all parties involved. By relying on these technologies, large-scale distributed energy systems can become more efficient and sustainable and beneficial for all. With each distributed unit as the participating group, the game adjustment coefficient can be selected as the performance adjustment weight coefficient to construct a competition model for large-scale distributed energy systems and optimize its solution algorithm, which has theoretical and practical significance for wide-area distributed energy systems. In this distributed energy system, energy storage plays an important role relating to reliability and safety, so research on energy storage technology also has great value. After the new energy is integrated into the grid, energy storage can facilitate the real-time balance of power, enhance the capacity factor of the system, improve the energy consumption capacity, cut peaks and fill valleys, and add another layer to the protective shell of nations' energy security [2,3]. With the explosive growth in installed capacity and power generation, coupled with the difficulties in transmission, distribution, and regulation, the support capacity of the new power system has become more demanding, and the new power system is clearly shifting from "source-grid-load" to "source-grid-load-storage". In this era of new energy, energy storage has become the fourth basic element of new power systems. Traditionally, new energy generation capacity is generally planned, and energy storage systems of corresponding capacity are allocated to solve the problem of power supply reliability. However, the above approach has narrow applicability; for example, it is not applicable to power transmission systems without local loads. With the popularization of new energy sources, more situations have arisen that require further technical innovation [4–7].

In [8], Michael Greaves introduced the concept of product lifecycle management to help companies make better decisions, improve efficiency, and increase innovation. Moreover, the concept of the digital twin was first clarified in this reference. An important point concerning digital twins is the association linking the physical and digital worlds, which makes it possible to realize a better simulation of physical quantities by unifying the virtual world with the real world. Thus, digital twin technology is an excellent way of integrating the virtual and real and optimizing the management of intelligence [9]. In [10], a digital twin-based framework for communication between a virtual smart grid and a real power system was proposed to address the life cycle process and deployed with sensor detection, fault diagnosis, and simulation computation. In [11], a novel framework based on a deep neural network was proposed that can provide the features of the operational state of the power grid with a small time delay and can be used for real-time online optimization. To accurately derive the main feature of the operational state of the power system, a data-driven model was proposed in [12] for the digital twin model with a recursive state and decreased performance evaluation.

Existing scheduling optimization strategies are divided into three main categories: centralized, point-to-point, and weakly centralized distributed [13]. For the centralized type, the author of [14] advocated the coordination of conventional units and new energy resources and proposed that smart grids would be affected by carbon emissions in the future. In [15], ten multi-objective algorithms were employed to search for the optimal Pareto front for an individual operator with the aim of addressing power quality and operation cost. The simulation results in this reference showed that the multi-objective algorithm could help reduce the power deviation by 45.9% compared to the engineering approach. While the above methods were all regulated by a central dispatch, recently, due to more new energy being deployed with the power grid, the grid is becoming more and more distributed and control over the smart grid is changing from centralized to distributed. For the weakly centralized distributed type, a reinforcement learning-based method was employed in [16] to solve the problem of the dimension for dispatches with numerous units. In [17], a multi-energy virtual power plant scheduling technology framework was proposed to address the problems of stochasticity and volatility in distributed resources, but a relevant discussion on the combination of the interaction process and game theory is missing. For decentralized optimization, a novel framework for the distribution of the dispatch model was established in [18] that can rapidly achieve consensus based on the leader-and-follower mode. This article introduced the concept of virtual tribes. One unit is selected as the form of distributed leadership, and the others are seen as the followers. Virtual tribes can be regarded as a form of distributed leadership and followership in smart grid systems. To achieve higher quality for consensus optimization, a reinforcement learning-based consensus method was proposed in [19]. In [20], a Stackelberg equilibrium-based multiagent learning method was developed to further search for the optimal dispatch scheme for the smart grid. In [21], a comparative analysis was conducted with the example of model predictive control, and the characteristics and advantages of centralized, non-collaborative, and collaborative distributed control methods were pointed out. In [22], a distributed optimal scheduling framework was constructed to address the difficulty of implementing a centralized model for a large-scale population of producers and consumers. In [23], the concept of the sharing economy was applied to a power system, and a master–slave game energy-sharing operation mechanism with producers, consumers, and virtual power plants was constructed. In [24], a producer–consumer transaction model was studied in a large-scale distributed energy and extensive information interaction scenario based on the framework of the power Internet of Things, but the network topology constraints of the distribution network system were not considered.

Taking advantage of digital twins and cooperative games, the operation state of a power grid can be simulated accurately and cooperative optimization quickly achieved. Therefore, in this paper, we combine digital twins and cooperative game collaborative optimization and provide methods from the perspective of wide-area distributed energy. The rest of this work is organized as follows. Section 2 describes the design of the mathematical model of wide-area distributed energy (WDE), which coordinates the conventional units and new energy resources. Section 3 discusses the specific implementation of cooperative game-based collaborative optimal regulation (CG-COR) for WDE. Section 4 provides the simulation results and test descriptions. Finally, Section 5 gives the conclusions of this paper.

2. Mathematical Model of WDE

2.1. Definition of a Digital Twin

The term "grid digital twin" refers to the digital space for the power system and the digital model of the physical object. The "grid physical-digital twin system" refers to the overall system composed of the corresponding physical objects and the digital twin. The WDE is the baseline for a digital twin grid framework, and it is interactive, deductive, and shared. "Shared" refers to the ability of the power system to share data through uniform standardization among digital twins. "Interactive" refers to the ability of the digital twin of the grid to develop autonomously and, in turn, guide the operation and manipulation of physical entity objects in the power system. "Deductive" refers to the inversion and prediction of the states of the physical entities of the power system in a virtual space.

2.2. WDE Dispatch Framework

The framework for digital twins for WDE is given in Figure 1. It has three subsystem models, which are the virtual mathematics model, the state of the physical grid, and the mutual communication model, respectively.

(1) Firstly, in the virtual mathematics model, the simulation model is very important for the accuracy of optimal scheme selection, and it generally collects the signal from the controller and the units' operation parameters from the monitors;

(2) Then, in the state of the physical grid model, the power disturbance, area frequency, and transmission line power of the power grid are obtained by sensors, and the model is prepared for real-time optimization for the power dispatch;

(3) Lastly, the mutual communication model is deployed with the regulation units and the controller, and this is the main operation for the dispatch optimization and the physical processing of the simulation model for WDE frequency regulation.

Specifically, the WDE involves the optimizers of the participant unit and the algorithm optimization. Frequency regulation in WDE consists of two operations. The first is a general conditioning command sent by the main grid to the WDE in cases of disturbance of the main grid by random variables. The second activity is that the WDE needs to assign general instructions to the county units through an optimum algorithm based on designated sets of rules. Figure 2 shows a schematic diagram of WDE that encompasses five different types (coal-fired [25], hydroelectric, liquefied natural gas (LNG) [26], wind turbine [27], and solar photovoltaic power plant [28]).

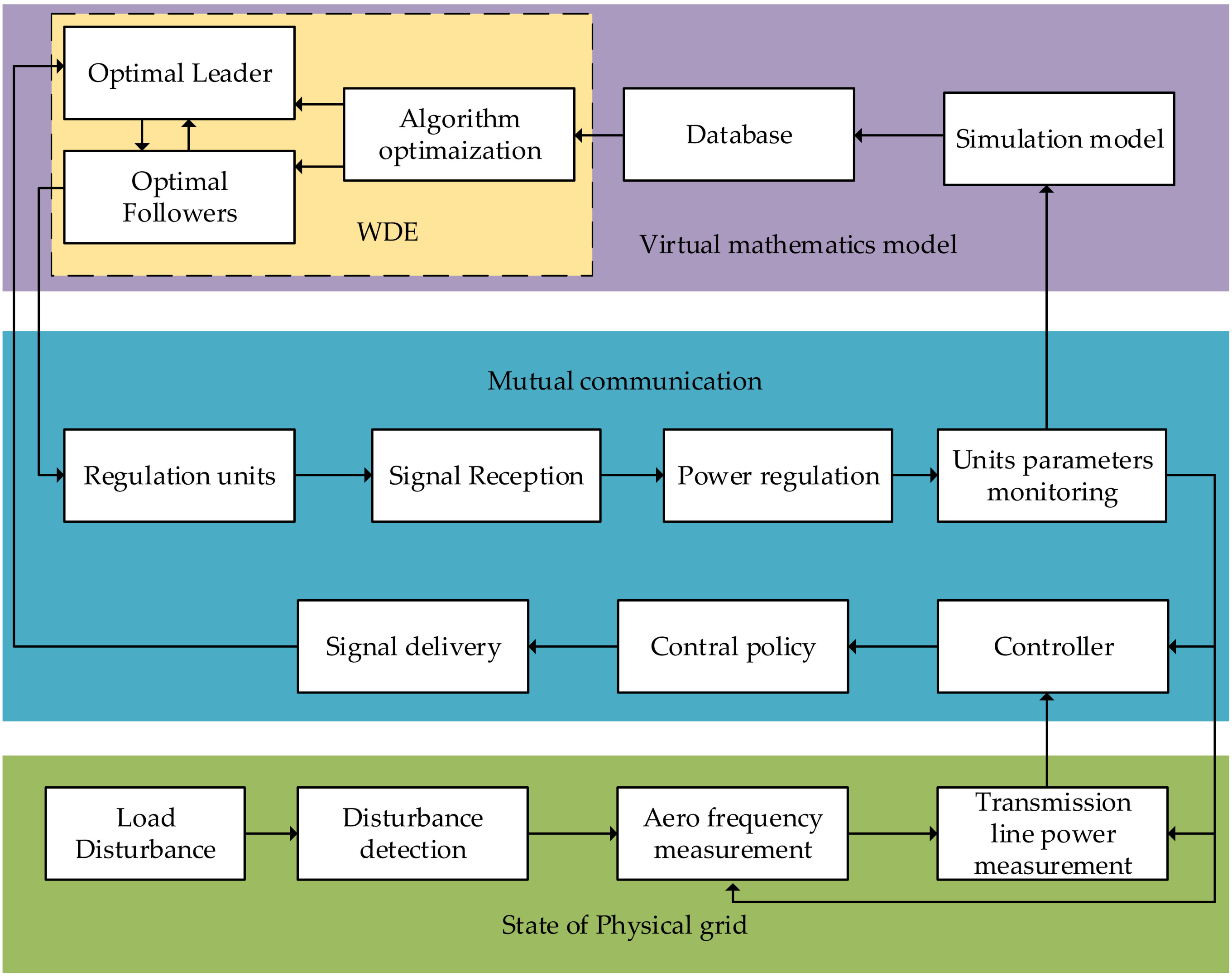


Figure 1. Framework for digital-twin WDE.

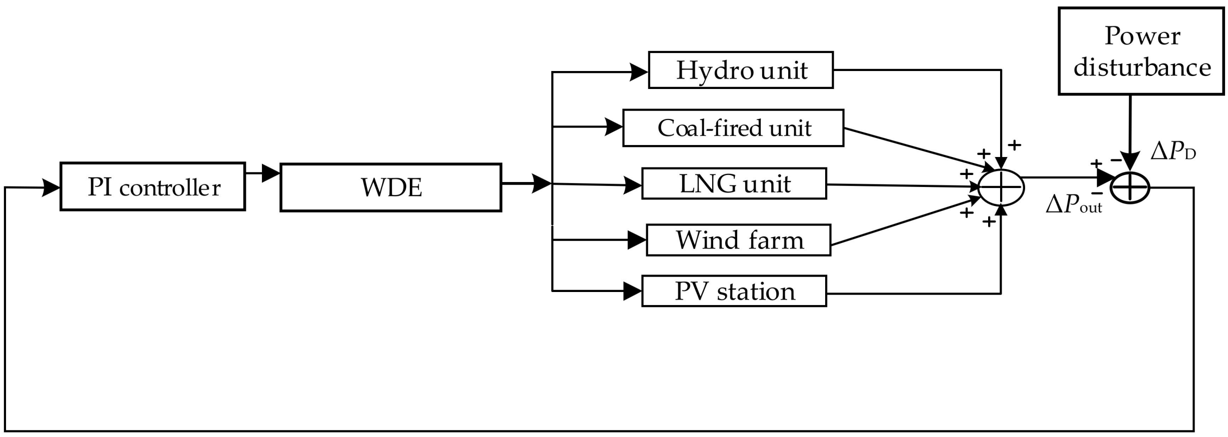


Figure 2. Framework of WDE.

2.3. Objective Function

Based on the obtained data, we can build a model of the physical system of a power system with distributed resources. The system can then be sensed and analyzed, which can effectively alleviate the drawbacks of the model drive being too cumbersome, resource-consuming, and slow to implement. To a certain extent, the model can be decoupled from the inline problem. The cooperative game is a type of game in which the participants make the gain of the cooperative body optimal by executing an enforced constraint agreement. In the digital twin of the grid for this WDE, the coupling between control signals and the integrated deployment of the hydro unit, coal-fired unit, wind farm, LNG unit, and PV station, which can make unified energy dispatch possible, improve the flexibility of the power dispatch and provide a more rational deployment of regulated units. Using the predicted method, the algorithm can better optimize adjacent control intervals to improve the performance of the dynamic optimal dispatch. Due to the fact that this paper is mainly focused on the dynamic regulation performance of WDE units, the optimization objective was to minimize the total power deviation between the regulation signal and the realistic power regulation output. Then, calculation of the objective functions should take account of the past control interval, current control interval, and the next adjacent control interval, as follows:

$$\min f = \sum_{k=1}^{N}\left|\Delta P_{\mathrm{m}}(k) - \sum_{i=1}^{n}\Delta P_i^{\mathrm{out}}(k+1)\right| \tag{1}$$

where $\Delta P_{\mathrm{m}}(k)$ is the predicted total power command at the kth control interval, $\Delta P_i^{\mathrm{out}}(k+1)$ is the optimal power output at the $(k+1)$th control interval according to the predicted total power command, N denotes the total number of control intervals in one service period, and n is the total number of regulation units for the WDE.

2.4. Constraints

In order to bring the model close to the prototype to form a digital twin, several relevant constraints need to be taken into consideration, including the coherence constraints of the regulation direction, electricity balance constraints, regulating capability constraints, and generation regulation constraints (GRCs), as follows:

$$\begin{cases} \Delta P_i^{\mathrm{in}}(k)\Delta P_{\mathrm{m}}(k) \geq 0 & (2) \\ \sum_{i=1}^{n}\Delta P_i^{\mathrm{in}}(k) - \Delta P_{\mathrm{m}}(k) = 0 & (3) \\ C_i^{\min} \leq \Delta P_i^{\mathrm{in}}(k) \leq C_i^{\max} & (4) \\ \left|\Delta P_i^{\mathrm{in}}(k) - \Delta P_i^{\mathrm{out}}(k-1)\right| \leq \Delta R_i \Delta T & (5) \end{cases}$$

Equation (2) is used as the consistency constraint for the regulation direction. To fully utilize the regulating unit, the regulating direction of the unit power command should have the exact same direction as the total regulating command at the kth control interval, where $\Delta P_i^{\mathrm{in}}(k)$ is the power input command to the ith WDE unit from the grid at kth control interval and $\Delta P_{\mathrm{m}}(k)$ denotes the signal from the main grid to the WDE. To ensure that the optimal scheduling scheme meets the regulation demand of the main network, Equation (3)—the power balance constraint—needs to be satisfied. At the kth control interval, the cumulative value of the power regulation input commands received by all WDE units should be exactly equal to the total value of the power regulation commands issued by the main network, with $C_i^{\min}$ and $C_i^{\max}$ being the minimum and maximum capacities of the ith WDE unit. The regulation capacity constraint for the units is shown in Equation (4). For the purpose of ensuring that the optimal scheduling scheme meets the actual operating conditions of the WDE units, the power regulation input commands received by all WDE units should exceed their minimum and maximum capacities at the kth control interval, with $C_i^{\min}$ and $C_i^{\max}$ being the minimum and maximum capacities of the ith WDE unit. Among the different types of WDE units, the dynamic response models of renewable energy sources (e.g., PV plants and wind turbines) have lower time delays and better regulation performance, while the dynamic response models of conventional units (e.g., coal-fired units, hydropower units, and LNG) must consider GRCs due to their poor regulation performance. If the GRCs and power limiters are considered, a realistic WDE unit output can be calculated, as shown in Equation (5), where $\Delta P_i^{\text{out}}(k)$ is the output power command received by the ith WDE unit at the kth control interval, ΔT represents the length of time at a control interval (generally about 4 s or 1 s), and ΔR_i is the maximum ramp rate of the ith unit.

3. Design of CG-COR for WDE

3.1. Framework of CG-COR for WDE

Since the whole grid is an interconnected whole, the objective function value of each distributed energy region depends not only on the actions of its internal nodes but also on the decision results for other regions within the region; i.e., the game of interests exists between regional grids. The game problem usually involves the following factors: the game participants, the payoffs for the game participants, and the strategies. The objective corresponds to the participants in the cooperative game, the optimization variables related to each objective correspond to the set of strategies controlled by each participant in the game, the objective value corresponds to the revenue of each participant in the game, and the constraints on the optimization problem restrict the value of the strategies of each participant in the game. CG-COR can be used for the further deployment of a WDE-based grid digital twin framework in order to achieve more rational and optimal allocation of regulation instructions. Since WDE takes the regulation commands of the past control interval and of the next adjacent control interval into account, the framework of CG-COR should contain two optimal steps (as shown in Figure 3), as follows:

(1) *Local optimizer deployment*: In the CG-COR framework for WDE, the optimizer is employed to search for the locally optimal result for WDE when the initial parameters for the optimization are created for CG-COR. Each unit is deployed with an optimizer (the optimal follower) and each unit simply communicates with the virtual optimal leader during the optimal process, which can help reduce the computation burden as the grid becomes more and more distributed;

(2) *Global scheme optimization*: Optimization of the described scheme is obtained by calculating the total power deviation between the two commands. One is the power input command from the grid to the WDE, and the other is the real power output of the WDE units (the cooperative game's participants) to the power grid. The global scheme optimization mainly concerns the results obtained by the local optimizers for each unit of the WDE. The communication between the optimal leader and each optimal follower can be realized using the mathematics model. As shown in Figure 4, when the global optimization receives the locally optimal results from the optimizers, the best fitness for the cooperative game in the current iteration will be selected according to the total power deviation. The optimal process for global scheme optimization can be given as follows:

    (a) A WDE unit can be regarded as a balanced unit due to the power balance constraint affecting the total units' input and the total power command (see Equation (3));
    (b) Then, the optimal results can be obtained for each unit when the cooperative game is performed well and the maximum benefit function has been reached;
    (c) Lastly, the data for the cooperative game are collected in a data center server (optimal leader), which is also the center for the creation of the initial parameters for the optimizer.

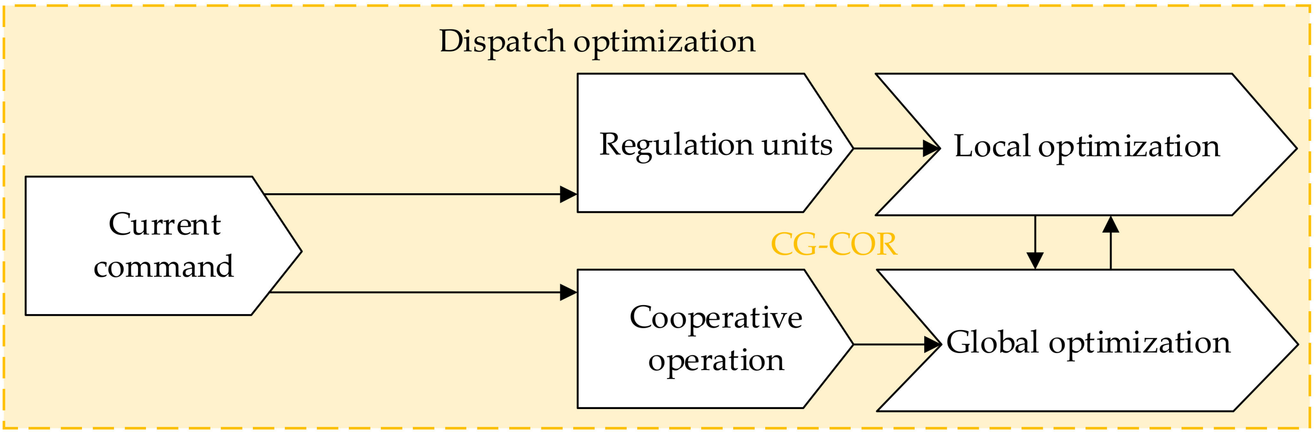


Figure 3. Framework of CG-COR.

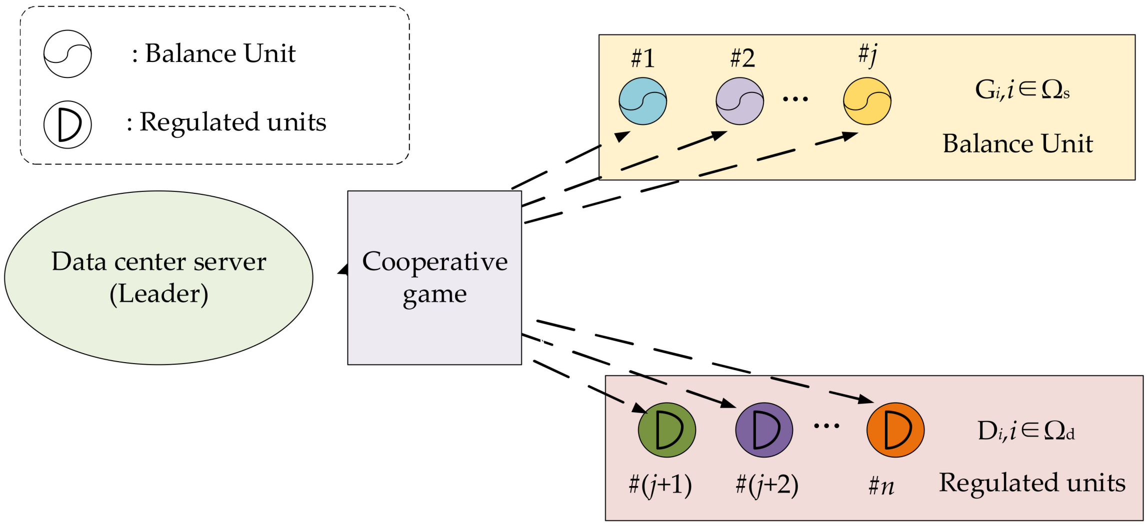


Figure 4. Schematic diagram of CG-COR for WDE.

3.2. Design of CG-COR

For the conventional optimization of WDE dispatch, the optimal task is allocated by the central dispatch, which needs the parameter of each unit and the operating state of the power grid. The dispatch assignment can be undertaken by the central dispatch with each unit disposed of with an optimizer, which can be seen as an intelligent body (follower). Each optimizer has its own optimal operation and the best dispatch scheme is selected by the central dispatch according to the cooperative game rules and the information from each follower. Moreover, the parameters of the followers are given by the leader after the global search in the last iteration. Typically, CG-COR mainly consists of seven operations, as follows:

(1) *Parameter initialization*: Set the dimensions of the problem D, maximum number of iterations T, and maximum number of optimizer iterations g. These parameters maintain the same values in an optimal search;

(2) *Population initialization*: Set the global optimal position X_{b} and calculate the global optimal fitness F_{b}. Firstly, the lower and upper bounds of all optimization variables are set as equal to the lower and upper adjustment capacities of each WDE unit, respectively. Then, an initialized population P_0 in the solution space $X_j = \Delta P_i^{\mathrm{in}}$ $(i = 1, 2, \ldots, n, j = 1, 2, \ldots, N)$ is generated according to proportions of the capacities, as follow:

$$X_0^i = \begin{cases} \frac{\Delta P_m(k)}{\sum_{i=1}^{n} C_i^{max}}\ , & if\ \Delta P_{\mathrm{m}}(k) < 0 \\ 0, & if\ \Delta P_{\mathrm{m}}(k) = 0 \\ \frac{\Delta P_m(k)}{\sum_{i=1}^{n} C_i^{max}}\ , & if\ \Delta P_{\mathrm{m}}(k) > 0 \end{cases} \tag{6}$$

where X_0^i represents the ith dimension of an initialized solution;

(3) *Local search*: For the local search, the initial parameter for each follower is formulated using the global optimal scheme. For the ith follower, the other followers' inputs remain the same in the optimal search and can be set as the value of the last iteration's solution in the global search. This can help reduce the computation time in the optimal search for the followers. According to the power balance constraint in Equation (2), an arbitrary unit can be regarded as the balanced unit. Firstly, according to the cooperative game framework, if only a unit's power command is set as the variable, the other n-2 units' power commands can be set to the fixed values of the global optimal solution X_0, and the balanced units can be given as $x_{\mathrm{b}} = \Delta P_{\mathrm{m}}(k) - \sum_{i=1(i\neq \mathrm{b})}^{n} \Delta P_i^{\mathrm{in}}(k)$. Then, an interior point method-based solver is set up to run n-1 iterations for each variable as a basis for a fast search for the global optimal solution for a single variable. Lastly, these optimal results are sent to the optimal leader for the next operation. The optimal formula is as follows:

$$\begin{cases} f_i(X_i) = \sum\limits_{k=1}^{N} \left| \Delta P_i^{in}(k+1) - \Delta P_i^{\mathrm{out}}(k+1) + \Delta P_{\mathrm{b}}^{\mathrm{in}}(k+1) - \Delta P_{\mathrm{b}}^{\mathrm{out}}(k+1) \right| & (7) \\ \quad \boldsymbol{s.t.}\ \ \Delta P_i^{\mathrm{in}}(k)\Delta P_{\mathrm{m}}(k) \geq 0 & (8) \\ \quad \Delta P_b^{in}(k)\Delta P_{\mathrm{m}}(k) \geq 0 & (9) \\ \quad C_i^{\mathrm{min}} \leq \Delta P_i^{\mathrm{in}}(k) \leq C_i^{\mathrm{max}} & (10) \\ \quad C_{\mathrm{b}}^{\mathrm{min}} \leq \Delta P_{\mathrm{b}}^{\mathrm{in}}(k) \leq C_{\mathrm{b}}^{\mathrm{max}} & (11) \\ \quad \left| \Delta P_i^{\mathrm{in}}(k) - \Delta P_i^{\mathrm{out}}(k-1) \right| \leq \Delta R_i \Delta T & (12) \\ \quad \left| \Delta P_{\mathrm{b}}^{\mathrm{in}}(k) - \Delta P_{\mathrm{b}}^{\mathrm{out}}(k-1) \right| \leq \Delta R_{\mathrm{b}} \Delta T & (13) \\ \quad i = 1, 2, \ldots, n, i \neq \mathrm{b} \end{cases}$$

$$\begin{cases} F_i(X_i) = f_i(X_i), & if\ C_b^{min} \leq x_b \leq C_b^{max} \\ F_i(X_i) = abs\left[\left(x_b - C_b^{max}\right)\left(x_b - C_b^{min}\right) \right] \cdot \varepsilon\ , & else \end{cases} \tag{14}$$

where f_i and F_i represent the objective function and the fitness function for the ith follower in its optimal search, respectively; $\Delta P_b^{in}(k)$ and $\Delta P_{\mathrm{b}}^{\mathrm{out}}(k-1)$ represent the power input command from the grid to the balanced unit in the WDE and the real power output of the balanced unit at the kth time control interval, respectively; $C_{\mathrm{b}}^{\mathrm{min}}$ and $C_{\mathrm{b}}^{\mathrm{max}}$ represent the maximum power input command and the minimum power output of the balanced unit, respectively; ΔR_{b} denotes the regulation power ramp for the balanced unit; and ε represents a faculty coefficient, which was set to 10^8 in this study;

(4) *Local search update*: The algorithm for the followers' solver can be implemented using the interior point method, which is updated with the barrier method;

(5) *Global scheme optimization*: For global optimization, the optimal leader obtains the optimal resources from each follower, and the best solution in the current iteration is selected according to the best fitness value. The n-1 local best solution at the tth iteration is given as $\overline{X}_i^t(i = 1, 2, \ldots, n, i \neq \mathrm{b})$ and local best fitness as $\overline{F}_i^t(i = 1, 2, \ldots, n, i \neq \mathrm{b})$, which help prepare for the following update;

(6) *Optimal location update*: The minimum value for the local best fitness as $\overline{F}_i^t$ is employed to update the current global optimal fitness F_{b} and the corresponding local best solution for the current global optimal position X_{b}. According to the cooperative game's rule, the optimal scheme with the best fitness value for the optimal leader is

selected. Then, the initial parameters for each optimizer are updated according to the optimal scheme created by the optimal leader. The optimal search continues in a cycle between steps (2)–(4) until the subsequent termination conditions satisfy the required settings;

(7) *Termination conditions*: If the current global optimal fitness F_t is larger than that of the last iteration F_b or the current iteration t reaches the maximum of iteration T, the optimal search is terminated.

3.3. Calculation Flow

The entire calculation flow for modeling WDE using CG-COR is provided in Algorithm 1.

Algorithm 1. The execution procedure for ARMA-GA for WDE.

1. **FOR1** k**:=1 to** N_t
2. Input the total power regulation command at the current control interval;
3. Initialize the parameters of CG-COR and its leader's solver;
4. **FOR2** t**:=1 to** T **or** $\overline{F}_i^t < F_b$
5. Send the optimal location and optimal fitness to the followers' solver;
6. **FOR3** i**:=1 to** n **(**$i \neq b$**)**
7. Update the variable location and the corresponding fixed value for optimization of the solver;
8. Initialize the solution for the ith follower and the corresponding optimal constraints from Equations (8)–(13);
9. **FOR4** j**:=1 to** g
10. Calculate the objective function value using Equation (7) with the constraints from Equations (8)–(13);
11. Calculate the fitness function value using Equation (14);
12. Update the location of the ith follower according to the barrier method for the interior point;
13. **END FOR4**
14. **END FOR3**
15. Select the globally optimal result according to the followers with the best fitness function;
16. Update the optimal location and optimal fitness for the next global search;
17. **END FOR2**
18. Update the units' output power to the grid;
19. **END FOR1**

4. Case Studies

In this study, a WDE model was developed to verify the superiority of the proposed algorithm through a comparison with the industrial proportional method (PROP) [15]. Table 1 shows the main parameters of the WDE units: coal-fired, LNG, wind farm (WF), and PV. The interior point method was employed for the solver. For the parameters of the CG-COR, the maximum number of iterations of the method was set to 200, and the maximum number of iterations of the interior method was set to 10. The simulation experiment was carried out on a personal computer using the MATLAB 2019b platform. The sampling time for the MATLAB platform was 0.01 s, the solver was ode 45, and the computer used an Intel(R) Core TM i7-8650U CPU.

Table 1. Main parameters of WDE units in area A of the two-area LFC model.

Unit No.	Type	Td (s)	ΔP^{rate} (MW/min)	ΔP_{max}(MW)	ΔP_{min}(MW)
G_1	Coal-fired	60	30	40	−20
G_2	LNG	20	18	20	−30
G_3	Hydro	5	150	10	−20
G_4	WF	1	—	15	−10
G_5	PV	1	—	10	−15

4.1. Statistical Test Experiments

4.1.1. Convergence for the Followers' Search

To verify the advantages of the proposed CG-COR, static tests were performed at three different powers. In these tests, the interior point method was employed to execute the followers' search for the WDE units. To analyze the influence of the iteration number for the local optimization on the convergence of the global optimization, different iteration numbers for the local optimizer were used in the simulation test. The experimental results are represented in Figure 5. The legend of Figure 5 presents the different settings for the local optimizer, and the lateral axis with the iteration number represents the convergence process of the global search. From Figure 5a, it can be seen that the convergence results for 10 and 15 generations tended to be the same, but the experiment required fewer iterations for the convergence with 15 generations. The number of iterations required to obtain suitable results for the 5 generation method was three times greater than that for the 15 generation method. In Figure 5b, the number of iterations required for convergence and the fitness optimization results were close for 15 and 10 generations in the experiment, but the 5 generation iterator was significantly inferior to the previous two generations in terms of the number of iterations required for the optimization process. As shown in Figure 5c, the 15 generation optimizer gave slightly better results than the 10 generation optimizer and had a more significant advantage over the 5 generation optimizer. When weighed in terms of the number of iterations required, the 5 generation optimizer clearly required more iterations than the 15 generation optimizer to obtain superior results, about ten times more. However, from the point of view of the time spent in the optimization process, the more generations were involved, the more time was consumed by the iterations and the slower the computation was. Lastly, the figures listed in Table 2 are the computation times at different power moments for the generations with 5, 10, and 15 iterations, respectively.

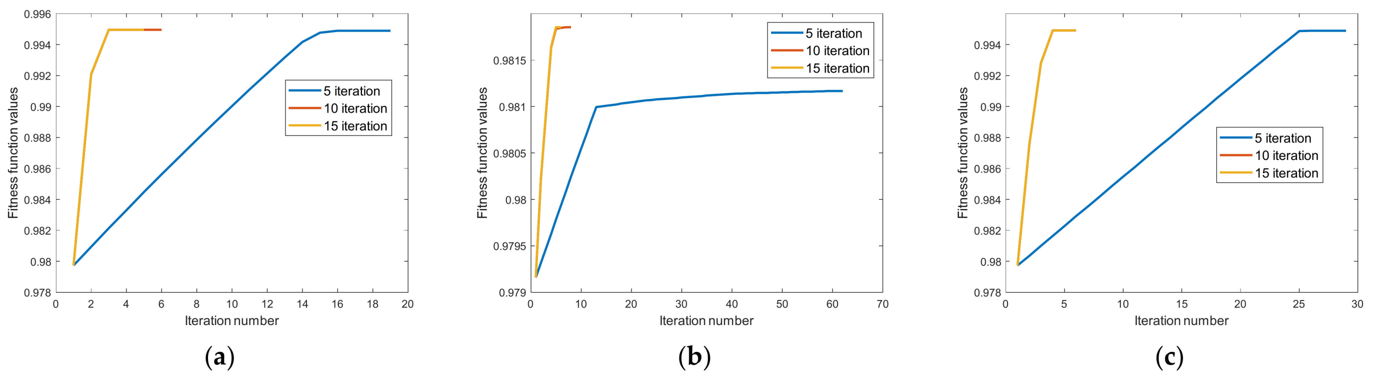


Figure 5. Comparison of accuracy of WDE models with different numbers of iterations. (**a**) $\Delta P_C = 40$ MW, (**b**) $\Delta P_C = 60$ MW, and (**c**) $\Delta P_C = 80$ MW.

Table 2. The computation times at different power moments for generations with 5, 10, and 15 iterations for the followers' optimizers.

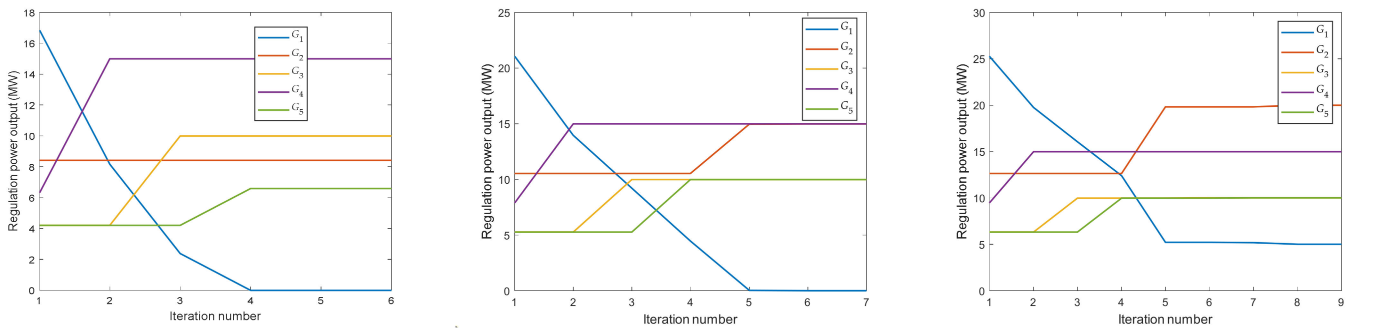
ΔP_D (MW)	5 Generations (s)	10 Generations (s)	15 Generations (s)
−80	4.322	0.305	0.166
−70	1.427	0.178	0.171
−60	0.859	0.278	0.239
−50	0.785	0.295	0.258
−40	0.538	0.322	0.278
−30	0.405	0.327	0.306
−20	0.336	0.229	0.275
−10	0.221	0.269	0.272
0	0.267	0.224	0.310
10	0.350	0.270	0.211
20	0.554	0.353	0.251

Table 2. *Cont.*

ΔP_D (MW)	5 Generations (s)	10 Generations (s)	15 Generations (s)
30	0.786	0.297	0.254
40	1.294	0.224	0.215
50	2.257	0.220	0.155
60	1.947	0.237	0.147
70	1.515	0.183	0.142
80	4.322	0.305	0.166

4.1.2. Optimal Power Command for Global Search

In this test, the corresponding load disturbance was applied in the power grid, and the power input command for the optimal followers in the optimal process is given in Figure 6. In the three statistical tests, the iterations for the followers' optimizer were set to ten. As shown in Figure 6, the globally optimal search for the optimal leader obtained high-quality results with fewer than ten iterations. In Figure 6a,b, the power command for G_1 (coal-fired unit) led to convergence to 0, while the power commands for G_4 (wind farm) and G_5 (PV) increased their maximum power output across the entirety of the optimal process. This indicates that the proposed method can help maximize the power output for new energy, such as PV and wind farms. In Figure 6c, the power output for the WF unit reaches capacity in two iterations. The power outputs for hydro and PV units increase to their maximum in three and four iterations. Lastly, the counterparts for the LNG and coal-fired units reach a power balance in nine iterations.



(**a**) (**b**) (**c**)

Figure 6. Power input commands for each follower obtained with their optimizers during the global optimal search for WDE. (**a**) $\Delta P_C = 40$ MW, (**b**) $\Delta P_C = 60$ MW, (**c**) $\Delta P_C = 80$ MW.

4.2. Statistical Test Experiments

4.2.1. Step Load Disturbance

For the step load disturbance test, several load disturbance simulation experiments ($\Delta P_D = -40$ MW, as given in Figure 7; $\Delta P_D = -50$ MW, as given in Figure 8; and $\Delta P_D = -60$ MW, as given in Figure 9) were conducted to verify the advantages of the proposed CG-COR. To analyze the effect of the algorithm applied to the WDE model, the proportional (PROP) method was used to perform comparative analysis experiments for each equivalent case. As shown in Figure 7a, application of the CG-COR method to the model resulted in a power deviation nearly four times smaller than that of the PROP method throughout the optimization process. The variation in the power deviation region under load disturbance is further illustrated in Figure 7b. From the figure, it can be seen that the total power command for PROP appeared overshoot, with an overshoot power regulation curve that first falls and then rises, while the proposed method obtained a non-overshoot power regulation curve with superior performance. In Figure 7c,d, two standard indices (area control error (ACE) and control performance standard (CPS1)) are shown to compare the optimal convergences with the two algorithms. From the figure, it can be seen that the proposed CG-COR can produce a power scheme with higher quality for the ACE and CPS1 indices, which means that the proposed method provides more optimal convergence in the optimization of WDE.

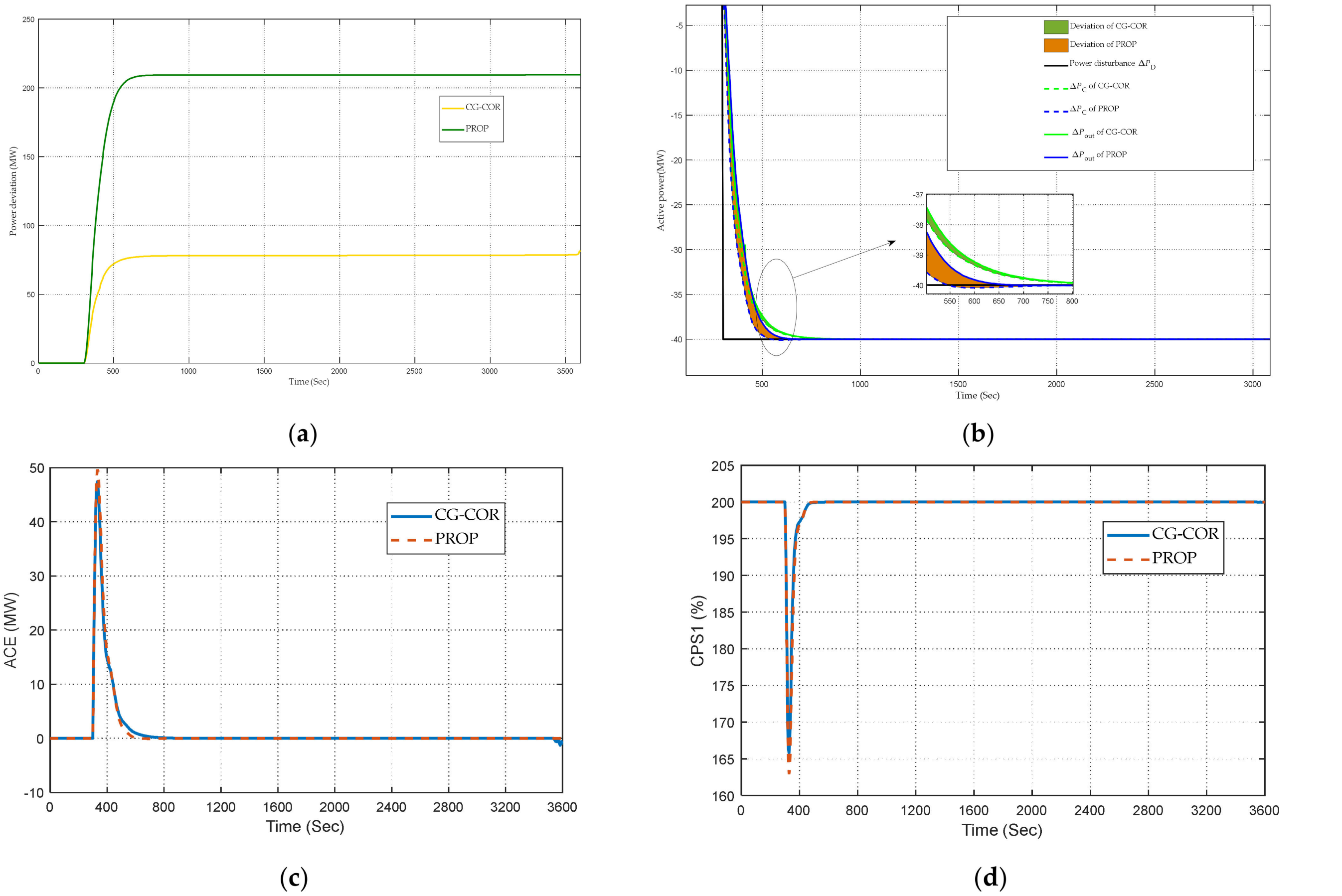


Figure 7. Real−time dispatch scheme obtained for the WDE dispatch model when $\Delta P_D = -40$ MW. (**a**) Variation in power deviation between the input power command and the actual power output. (**b**) Area change for power deviation with the load disturbance. (**c**) The area control error (ACE) change curve for the two algorithms during the process. (**d**) The control performance standard (CPS1) change curve for the two algorithms during the process.

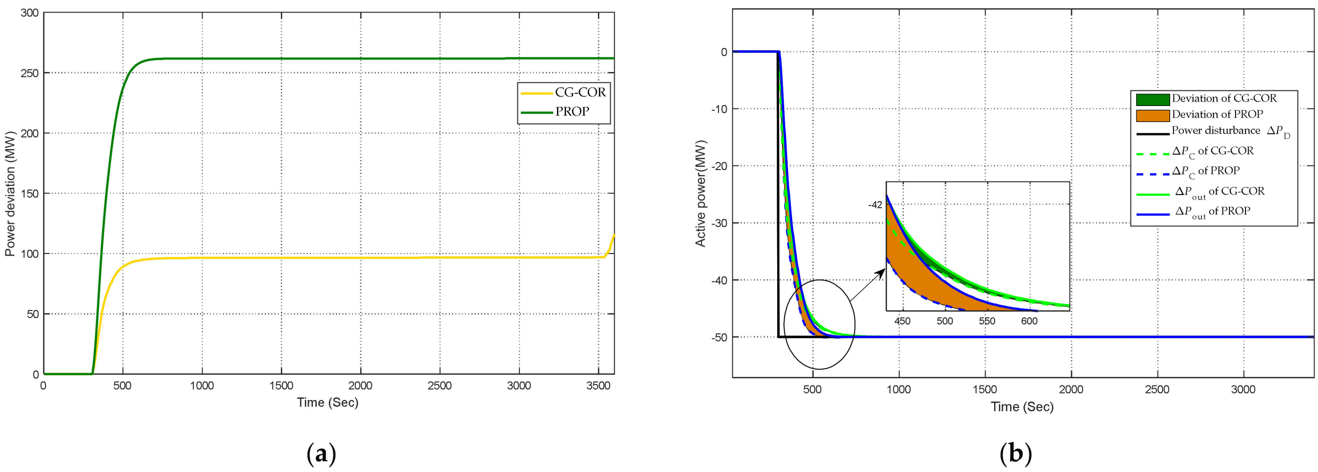
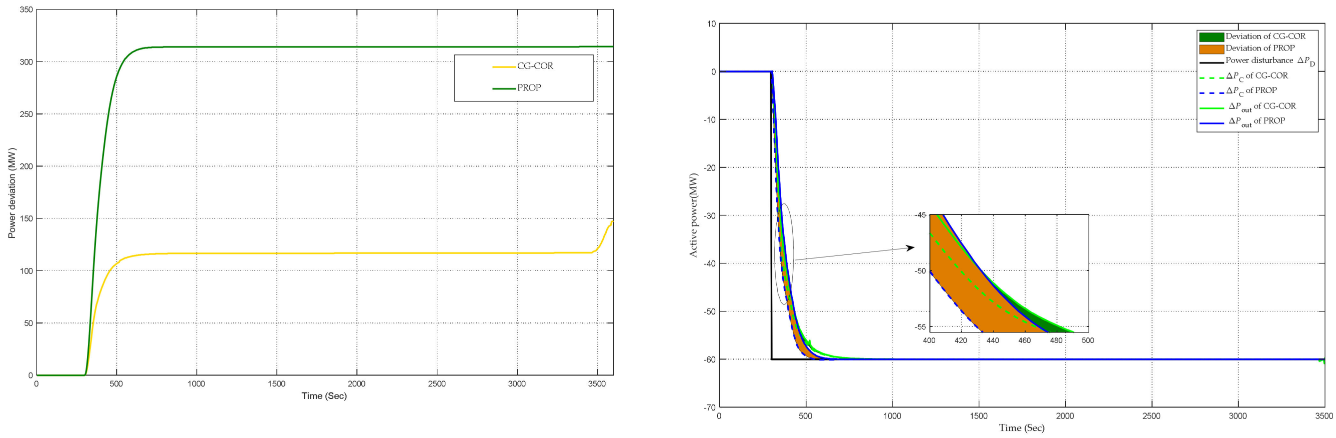


Figure 8. Real−time dispatch scheme obtained for the WDE dispatch model when $\Delta P_D = -50$ MW. (**a**) Variation in power deviation between the input power command and the actual power output. (**b**) Area change for power deviation with the load disturbance.



(**a**) (**b**)

Figure 9. Real−time dispatch scheme obtained for the WDE dispatch model when $\Delta P_D = -60$ MW. (**a**) Variation in power deviation between the input power command and the actual power output. (**b**) Area change for power deviation with the load disturbance.

As shown in Figure 8a, the proposed method resulted in a smaller power deviation than the PROP method across the whole optimization. Further description of the change in the total power deviation is given in Figure 8b, which shows that a non-overshoot power regulation curve was obtained with the proposed method, while an overshoot power regulation curve was acquired with the PROP method.

From Figure 9, it can be seen that the area for the power deviation obtained with the PROP method covered that of CG-COR, indicating that the CG-COR algorithm could effectively reduce the power deviation in the optimization process; moreover, it can be easily seen from the figure that CG-COR had a lower total power command than the PROP algorithm.

4.2.2. Continuous Step Load Disturbance

In the following continuous test, for further validation of the performance of the CG-COR model, we implemented a more random load disturbance that more closely resembled the actual variation in load and power users (as shown in Figure 10). Similarly, a lower total power deviation was obtained between the input power command and the actual output profile, as can be seen in Figure 10a. It is noteworthy that, as Figure 10b shows, a non-overshoot actual output power curve was obtained with the proposed method across the whole of the optimal dispatch process, which means that the CG-COR can effectively coordinate the regulation performance of the regulated units and obtain a high-quality dispatch scheme for the power grid. Figure 10 shows a schematic of the CG-COR for WDE. Moreover, in Figure 10c,d, the ACE and CPS1 indices are given for comparison with the optimal convergence for the two algorithms. There is no doubt that the proposed method could obtain a CPS1 curve (Figure 10c) with lower magnitudes and a slower peak for the ACE curve (Figure 10d) than the conventional PROP method. The regulation amounts for the energy with five resources obtained by the two algorithms are given in Figure 10e,f. It is obvious that the power dispatch scheme obtained with CG-COR could maximize the energy output from the wind and PV units and keep the coal-fire output stable.

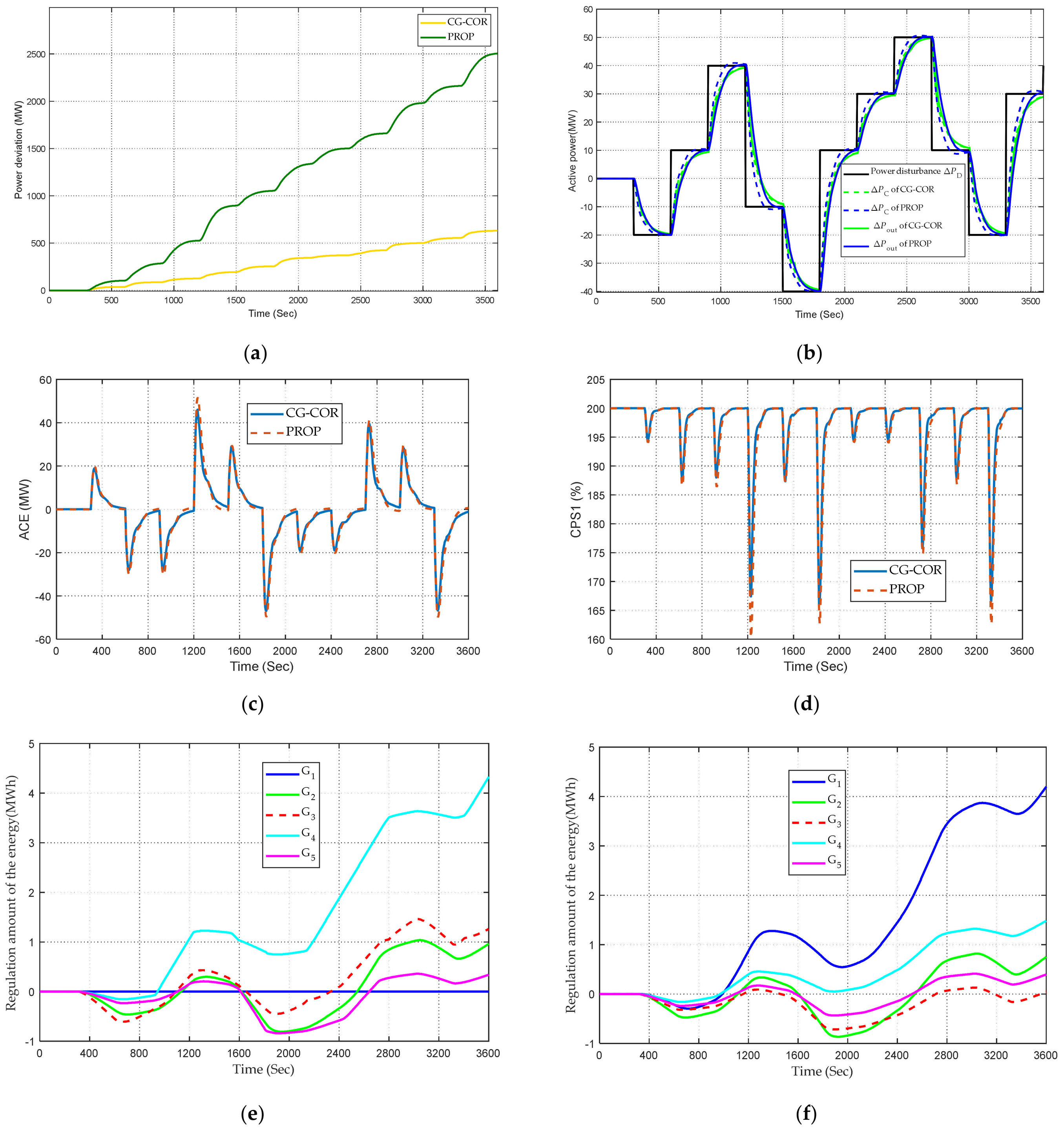


Figure 10. Real−time dispatch scheme obtained with the WDE dispatch model when using a random load disturbance. (**a**) Variation in power deviation between the input power command and the actual power output. (**b**) Random load disturbance and regulation curves. (**c**) The area control error (ACE) change curve during the process for the two algorithms. (**d**) The control performance standard (CPS1) change curve during the process for the two algorithms. (**e**) The regulation amount for the energy obtained with the CG-COR method. (**f**) The regulation amount for the energy obtained with the PROP method.

Lastly, Table 3 shows the simulation results from the four tests mentioned above. The method column includes a power grid with a single WDE unit, CG-COR with multiple WDE units, and PROP with multiple WDE units. As the table shows, there is no doubt that higher control performance was obtained for the grid with multiple WDE units than with a single WDE unit. It is obvious that the scheduling scheme obtained with the proposed method could not only be resolved quickly in time but the solution obtained was of higher quality. In terms of performance, the proposed method improved the accuracy for the intensity of the closeness between the total power input command and total power output curve. To be specific, the proposed method helped reduce the total power deviation by about 61.1%, 55.7%, 53.1%, and 74.8%.

Table 3. Comparison of results for online optimization with different disturbances.

ΔP_D	Method	Accuracy (%)	Deviation (MW)
−40 MW	CG-COR	91.32	81.60
	PROP	90.96	209.65
	Single WDE	89.32	804.28
−50 MW	CG-COR	91.29	116.00
	PROP	90.96	262.02
	Single WDE	89.32	1005.27
−60 MW	CG-COR	91.28	147.59
	PROP	90.96	314.43
	Single WDE	89.32	1260.80
Disturbance 1 (see Figure 10a)	CG-COR	88.23	631.18
	PROP	79.18	2504.87
	Single WDE	62.74	6675.08

5. Conclusions

To summarize, this paper makes the following four contributions:

(1) A digital twin-based WDE model is proposed that can fully coordinate all regulated units and fully considers and rationally utilizes new energy units;
(2) A form of cooperative game optimization-based WDE scheduling is proposed that can reasonably allocate power commands for multiple control resource systems. The proposed leader-and-follower mode can help reduce the optimization time due to the distributed optimization process;
(3) Through the simulation and comparison experiments performed with the WDE model, it was found that the optimal WDE scheduling scheme based on the cooperative game optimization algorithm could solve the scheduling problem more effectively;
(4) The proposed CG-COR model could effectively coordinate the regulation resources for WDE units. It enhanced the intensity of the closeness between the total power input command and output curve, and it reduced the total power deviation by 61.1%, 55.7%, 53.1%, and 74.8%, respectively.

Based on the current technology and research directions, future research could include the following:

(1) As the number of electric vehicles is likely to increase significantly in the future, the master–slave game could be considered to rationally guide the charging and discharging of electric vehicles and reduce the cost of electricity;
(2) A large number of flexible loads are involved in the operation of power systems, resulting in convenience for the demand response, while the game model becomes more complex. Therefore, it is necessary to study the demand response based on an incomplete information game;
(3) Power losses will be considered in a future study. The optimization will take into account factors such as transmission and conversion losses. The topology of the grid and regulation resources will also be analyzed in a future study.

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Nomenclature

ACE	area control error
CPS1	control performance standard
CG-COR	cooperative game-based collaborative optimal regulation
GRC	generation regulation constraint
LNG	liquefied natural gas
PROP	proportional method
PV	photovoltaic
WDE	wide-area distributed energy
WF	wind farm

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