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An Economic Dispatch Method of Microgrid Based on Fully Distributed ADMM Considering Demand Response

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Abstract: Aiming at the problem that the existing alternating direction method of multipliers (ADMM) cannot realize totally distributed computation, a totally distributed improved ADMM algorithm that combines logarithmic barrier function and virtual agent is proposed. We also investigate economic dispatch for microgrids considering demand response based on day-ahead real-time pricing (RTP), which forms a source-load-storage collaborative optimization scheme. First, three general distributed energy sources (DERs), renewable energy resources (RESs), conventional DERs and energy storage systems (ESSs), are considered in the method. Second, the goal of economic dispatch is to minimize the sum of three energy generation costs and implement the optimal power allocation of dispatchable DERs. Specifically, the approach not only inherits the fast computational speed of ADMM but also uses barrier function and virtual agent to handle inequality and equality, respectively. Moreover, the approach requires no coordination center and only the communication between current agent and adjacent agent to achieve totally distributed solution for every iteration, which can preserve information privacy well. Finally, a 30-node microgrid system is used for case analysis, and the simulation results demonstrate the feasibility and effectiveness of the proposed approach. It can be found that, the proposed approach converges to the optima when $p = 0.01$, $v = 100$, $t^0 = 0.01$ and $\mu = 2$.

Keywords: microgrid; distributed control; ADMM; demand response; logarithmic barrier function; virtual agent

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1. Introduction

Given increasingly serious environmental pollution and the gradual exhaustion of fossil fuel, there is a trend in the development of energy systems to be cleaner and more intelligent. The development of smart energy sources has become a national strategy [1], and the energy structure adjustment strategy is advancing rapidly. The key point of smart energy source is proper management of distributed energy sources (DERs) [2]; therefore, microgrids [3] have quickly developed as an effective way method of DER consumption because of its merits of clean energy, flexible power generation, energy storage, compatibility with the environment, low line loss, etc. [4]. The microgrid contains multiple types of DERs, such as wind turbines (WT), photovoltaic generation systems (PV), diesel generators (DG) and energy storage systems (ESSs). The economic dispatch [5] of microgrid is to achieve the optimal allocation of DERs through a series of algorithms and strategies, which can efficiently alleviate the shortage of energy supply and environmental pollution. Therefore research on economic dispatch of microgrids is quite important.

The goal of economic dispatch of microgrids is mainly to minimize generation cost while meeting power generation constraints and power balance constraints in order to achieve optimal power allocation of DERs. Renewable energy sources (RESs) can be wasted to different degrees in the general economic dispatch of microgrids. In order to absorb and reduce the abandonment rate of WT and PV, the introduction of demand response in the economic dispatch of microgrids [6] is a very effective measure that can not only increase the wind and solar consumption rate but also adjust the electricity consumption behavior of users; the interconnection and interaction between the power generators and the users has also been realized. An incentive-based demand response plan for economic dispatch of microgrids was introduced in [7]. In [8], the authors proposed a real-time incentive demand response algorithm for smart grid systems with reinforcement learning and deep neural networks to ensure the balance of power supply and demand and improve grid reliability. In addition to incentive mechanisms, demand response also uses price mechanisms to guide users' electricity consumption behavior. A real-time price (RTP) decision model was developed to implement the demand response, effectively minimized the generation cost [9]. In [10], the authors proposed an energy management system strategy by introducing price-based demand response to reduce the operating cost of the entire microgrid. Considering price-based demand response can make users more voluntarily and actively participate in the adjustment of electricity consumption by changing electricity prices, in this study, we chose it in the economic dispatch to construct a source-load-storage coordination scheme.

It is important to implement the economic dispatch problem for microgrids after forming it is established. The implementation effect of economic dispatch of microgrids is related to the applied control structure. Control structure that are used widely in microgrids can be divided into two types: centralized control and distributed control. However, with the penetration of DERs, centralized control wherein a central controller is responsible for communication with all other DERs faces challenges such as heavy computational burden and complex communication. Thus, distributed control will emerge as the times require. Economic dispatch under a distributed control [11] structure requires no central controller [12] and allocates the local controller for each DER. Finally, all DERs can complete economic dispatch only through point-to-point communication with adjacent agents. Therefore, the reliability of distributed control is higher, and coupled with the distributed characteristics of high dispersion and easy deployment of DERs in the microgrid, distributed economic dispatch has gradually become a research hotspot.

Existing literature includes a lot of research on distributed economic dispatch. An economic dispatch strategy of microgrids was proposed in [13] based on distributed control by introducing the principle of equal increment rate. In [14], a consensus algorithm in the isolated microgrid was proposed to solve reactive power distribution. Considering the pros and cons of the principle of equal increment rate and consensus algorithm, an adaptive dual-control energy internet optimization method combining the two theories above was proposed in [15]. Although these distributed economic dispatch methods avoid the problems of heavy calculation and complicated communication of centralized control, further research and improvement are required in terms of the number of iterations and convergence speed. Based on the above problems, Boyd et al. [16] first proposed the alternating direction method of multipliers (ADMM) algorithm based on the multi-agent framework to solve the distributed optimization problem. Compared with other distributed optimization algorithms, the ADMM algorithm has faster convergence speed, which integrates the decomposability of dual ascent [17] and the faster convergence rate of the multiplier method, requiring no strong convex properties for objective function. Therefore, it has become a very important method for distributed optimization. In [18], a coordinated planning method of transmission and distribution network based on the standard ADMM algorithm was proposed. A distributed ADMM algorithm was developed in [19] by applying finite-time average consensus algorithm to solve economic dispatch problems. In [20], a GS-ADMM algorithm was proposed that can achieve sequential optimization based on standard the ADMM algorithm. Aiming at the problem of a possible longer waiting time in sequential optimization described in [20], a proximal Jacobian ADMM algorithm that can realize optimal power flow problem by parallel optimization was introduced in [21]. However, these methods cannot be called true distributed computing. They still need a coordination center to update the variable value of each agent, causing the traditional ADMM algorithm to still be subject to the computation and communication capabilities of the coordination center. Thus, several fully distributed ADMM algorithms were proposed to solve the above problem. An appropriate energy management framework in smart islands based on the primal-dual method of multipliers was established in [22]. Due to a lack of discussion of coupled constraint in [22], a fully distributed scheme that embeds a dynamic average consensus protocol in the ADMM was designed to minimize the sum of local objective functions in [23]. An ADMM algorithm that makes some improvements on the algorithm in [23] to speed the converging rate based on duality and consensus theory was proposed in [24] to solve such linearly constrained convex optimization problems. Although these algorithms can achieve fully distributed computation, they tend to concern the processing of equality and ignore the processing inequality. In order to consider both equality and inequality, an improved fully distributed ADMM algorithm based on logarithmic barrier function and virtual agent is proposed in this paper that realize fully distributed economic dispatch of microgrids. In contrast to existing ADMM algorithms, the differences and our main contributions are summarized as follows.

(1) The logarithmic barrier function method and the idea of virtual agent are employed to deal with the power inequality constraints of the distributed power sources and the power balance equality constraints of the microgrid in this paper, by which the problem of constraints is solved easily by reducing the complex computation and simplifying the solution process.
(2) The algorithm requires no coordination center, and the update of each variable only requires the value of the adjacent agent's variable to complete calculation, which can realize fully distributed computation and preserve information privacy well.
(3) Through comparison with the traditional ADMM algorithm, the feasibility and effectiveness of the proposed method are verified. Sensitivity analysis of the related parameters is implemented, which can ensure the convergence of the proposed algorithm.
(4) A fully distributed source-load-storage coordination scheme is constructed under the price-based demand response, and real-time optimal dispatch results can be obtained that use the power of the RESs as soon as possible and implement the beneficial interaction between power generators and power users.

The remainder of the paper is organized as follows. Section 2 presents the mathematical formulation of the economic dispatch problem. A fully distributed ADMM algorithm and a source-load-storage collaborative optimization scheme are proposed in Section 3. Case studies and the simulation results are elaborated in Section 4. Section 5 presents conclusions and future research directions.

2. Mathematical Formulation

The microgrid structure is shown in Figure 1, which contains a PV, a WT, four DGs, two ESSs and some loads. DG and ESS are dispatchable, whereas RESs are not dispatchable because their output power is related to the external environment and cannot be controlled. Thus, we expected maximized power generation consumption of RESs in economic dispatch, independent of power generation cost [3].

The following optimization problems are formulated according to the structure in Figure 1.

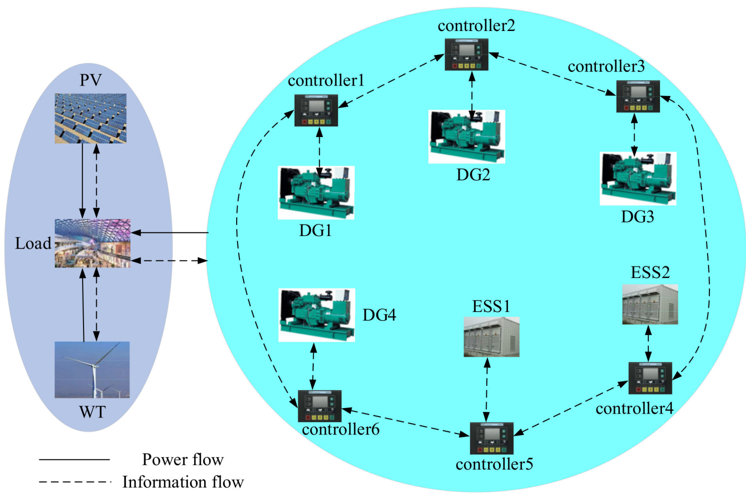

Figure 1. Microgrid structure.

(1) DG

DG can adjust its power to any required reference value within the power limit. The cost function is usually expressed as a quadratic function [25],

$$f_{DG,k}(t) = a_k P_{DG,k}^2(t) + b_k P_{DG,k}(t) + c_k \tag{1}$$

$$P_{DG,k}^{min} \le P_{DG,k}(t) \le P_{DG,k}^{max} \tag{2}$$

$$-P_{DG,k}^{R} \le P_{DG,k}(t) - P_{DG,k}(t-1) \le P_{DG,k}^{R} \tag{3}$$

where a_k,b_k and c_k are the coefficients of cost function $f_{DG,k}(t)$; $P_{DG,k}(t)$ is the power output of the k-th DG at time t; $P_{DG,k}^{max}$ and $P_{DG,k}^{min}$ are the maximum and minimum power output of DG, respectively; and $P_{DG,k}^{R}$ is the maximum ramp rate of DG.

(2) ESS

ESS has the function of bidirectional regulation of energy in the microgrid. It exchanges electrical energy with the microgrid through power electronic devices, and its cost function is defined as [26,27]:

$$f_{ESS,j}(t) = a_j P_{ESS,j}^2(t) + b_j P_{ESS,j}(t) + c_j \tag{4}$$

$$\begin{aligned} & -P_{ESS,j}^{max} \le P_{ESS,j}(t) \le P_{ESS,j}^{max} \\ & P_{ESS,j}(t) = \begin{cases} P_{ESS,c,j}(t), & P_{ESS,j}(t) \le 0 \\ P_{ESS,\mathrm{dc},j}(t), & P_{ESS,j}(t) > 0 \end{cases} \\ & P_{ESS,c,j}(t) * P_{ESS,\mathrm{dc},j}(t) \ne 0 \end{aligned} \tag{5}$$

where $P_{ESS,j}(t)$ is the charging/discharging power of the j-th ESS at time t; $P_{ESS,c,j}(t)$ and $P_{ESS,\mathrm{dc},j}(t)$ are the charging power and discharging power, respectively; a_j, b_j and c_j are the coefficients of cost function $f_{ESS,j}(t)$; and $P_{ESS,j}^{max}$ is the maximum of charging/discharging power.

The optimal power allocation in the microgrid is aimed at allocating the power output by minimizing generation cost and satisfying the constraints of the power balance, as well as the DERs' own power generation. The economic dispatch problem considered in this paper can be formulated as an optimization problem in Equation (6).

$$\begin{cases} \min\limits_{P} \sum\limits_{t \in T} \left(\sum\limits_{k \in N_{DG}} f_{DG,k}(t) + \sum\limits_{j \in N_{ESS}} f_{ESS,j}(t) \right) \\ s.t. \quad P_{DG}(t) + P_{ESS}(t) + P_{WT}(t) + P_{PV}(t) = P_D(t) \\ \qquad and \quad (2), (3), (5) \end{cases} \tag{6}$$

where T is the total number of time slots; N_{DG} and N_{ESS} are the total number of DGs and ESSs, respectively; and $P_{WT}(t)$ and $P_{PV}(t)$ are the power output of WT and PV, respectively.

In order to solve the economic dispatch problem from the generation and consumption side, which can improve the interaction of sources and loads and enhance the utilization of the RESs. Load demand is obtained by utilizing the principle of demand response (DR) based on a pricing mechanism. The DR modeling is introduced as follows.

(3) DR MODELING

It is known that there are three electricity pricing mechanisms in price-based demand response: time-of-use pricing (TOU), critical-peak pricing (CPP) and real-time pricing (RTP). Considering the traits of day-ahead real-time pricing (DARTP), we chose it as the pricing mechanism to implement demand response in this paper.

The purpose of demand response is to adjust the electricity consumption of users by reasonably setting electricity prices. Therefore, a better characterization of users' electricity consumption behavior is particularly critical for achieving demand response. Price-based demand response generally uses the power elasticity matrix [28] to describe the relationship between users' power consumption and market electricity prices. Formula (7) reflects the relationship between the change rate of electricity consumption and the change rate of electricity price.

$$\begin{bmatrix} \Delta d_1/d_1 \\ \Delta d_2/d_2 \\ L \\ \Delta d_{24}/d_{24} \end{bmatrix} = E \begin{bmatrix} \Delta pr_1/pr_1 \\ \Delta pr_2/pr_2 \\ L \\ \Delta pr_{24}/pr_{24} \end{bmatrix} \tag{7}$$

where Δd_i and Δpr_i are changes in demand and price, respectively, during time slot i; d_i and pr_i are the base load demand and electricity price, respectively, during time slot i; and $\boldsymbol{E}$ is the price elasticity matrix, which can be described as:

$$\boldsymbol{E} = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \cdots & \varepsilon_{1,24} \\ \varepsilon_{2,1} & \varepsilon_{2,2} & \ddots & \varepsilon_{2,24} \\ \vdots & \ddots & \ddots & \vdots \\ \varepsilon_{24,1} & \varepsilon_{24,2} & \cdots & \varepsilon_{24,24} \end{bmatrix} \tag{8}$$

where $\varepsilon_{i,i}$ is the self-elasticity coefficient, and $\varepsilon_{i,j}(i \neq j)$ is the crossing elasticity coefficient.

The change of load demand in any period of time can be obtained by the equivalent transformation of Formula (7).

$$\Delta d_i = \sum_{j=1}^{24} \left(\varepsilon_{i,j} \times \left(\Delta pr_j/pr_j\right) \times d_i\right) \tag{9}$$

The price changes according to the difference of between load demand and RESs,

$$\Delta pr_t = \beta(d_t - P_{WG}(t) - P_{PV}(t)) \tag{10}$$

where β is the DARTP proportional coefficient, and t represents the same time slot as i.

The load demand after DARTP-DR implementation can be expressed as:

$$d_{DR-t} = d_i + \Delta d_i \tag{11}$$

In order to ensure that the demand response has a positive effect on the economic operation for the microgrid, the amount of load change needs to meet certain constraints.

From Formulas (9)–(11), it can be seen that the amount of load change can be divided into the amount of shifting out and the amount of shifting in.

$$\Delta d_{shift-out} = \sum_{i=1}^{24} m\Delta d_i,\ if\,\Delta d_i < 0, m = 1;\ else\ m = 0 \tag{12}$$

$$\Delta d_{shift-in} = \sum_{i=1}^{24} n\Delta d_i,\ if\,\Delta d_i > 0, n = 1;\ else\ n = 0 \tag{13}$$

If $\left|\Delta d_{shift-out}\right| \geq \left|\Delta d_{shift-in}\right|$, the amount of load change is corrected as:

$$\begin{cases} \Delta d_i' = \Delta d_i & \Delta d_i > 0 \\ \Delta d_i' = \Delta d_i \times \Delta d_{shift-in} / \Delta d_{shift-out} & \Delta d_i < 0 \end{cases} \tag{14}$$

If $\left|\Delta d_{shift-out}\right| < \left|\Delta d_{shift-in}\right|$, the amount of load change is corrected as:

$$\begin{cases} \Delta d_i' = \Delta d_i & \Delta d_i < 0 \\ \Delta d_i' = \Delta d_i \times \Delta d_{shift-out} / \Delta d_{shift-in} & \Delta d_i > 0 \end{cases} \tag{15}$$

where $\Delta d_{shift-out}$ and $\Delta d_{shift-in}$ are the amount of shifting out and the amount of shifting in, respectively, of load demand.

We substitute Formula (11) into Formula (6) to obtain the dynamic economic dispatch problem.

$$\begin{cases} \min\limits_{P} \sum\limits_{t\in T} \Big(\sum\limits_{k\in N_{DG}} f_{DG,k}(t) + \sum\limits_{j\in N_{ESS}} f_{ESS,j}(t) \Big) \\ s.t. \quad P_{DG}(t) + P_{ESS}(t) + P_{PV}(t) + P_{WG}(t) = d_{DR-t} \\ \qquad and \quad (2), (3), (5) \end{cases} \tag{16}$$

3. Distributed ADMM Algorithm for Dynamic Economic Dispatch

3.1. Optimal Model Processing

From Formula (16), the optimization model contains two kinds of constraints: inequality and equality constraints. The logarithmic barrier function and the idea of virtual agent are employed to deal with the constraints of the optimization problem in this paper.

(1) Process of Inequality Constraints

The goal processing of inequality constraints is mainly to use the barrier function method to add the barrier function to the original objective function, which can limit the solution of the objective function to the feasible range. The barrier function generally has two forms: fraction and logarithm. Considering that the derivation result of the fractional form is more complicated, the logarithmic barrier function is chosen to deal with inequality constraints.

(2) Process of Equality Constraints

Equality constraints describe the relationship of all variables. In this paper, we use the idea of virtual agents to solve this problem.

Definition of virtual agent: virtual agent refers to a conceived agent whose cost function is a constant function; there is no optimization variable, but it meets specific constraints.

From the definition of the virtual agent, we know that as long as the cost function of the virtual agent is set as 0, the objective function plus the equality constraint not only has no influence on the overall solution result but also makes the result meet the specific constraints. There are two advantages for this processing: (1) each agent is only responsible for satisfying its own power constraints; and (2) the virtual agent is responsible for satisfying the overall power balance constraints.

Before introducing the details of processing the optimization model [29], Problem (16) is considered again. In order to unify the form, the optimization objective function can be set as $f(P)$; the lower and upper bounds of the inequality constraint are represented by $\underline{h}$ and $\overline{h}$, respectively; and the time index is dropped for convenience. Then, Problem (16) can be written as:

$$\begin{cases} \min\limits_{P} \quad f(P) = \sum\limits_{i=1}^{n} f(P_i) \\ s.t. \quad \sum\limits_{i=1}^{n} P_i = d_{DR} - P_{RES} \\ \qquad \underline{h}_i \leq P_i \leq \overline{h}_i \end{cases} \tag{17}$$

where P_i is the power output of each dispatchable DER.

$$\begin{aligned} &\min_{x} \sum_{i=1}^{\omega} g_i(x) \\ &g_i(x) = t f_i(x) + f_i(x) \\ &f_i(x) = \begin{cases} -log(-\underline{h}_i + P_i) - log(\overline{h}_i - P_i) \\ \qquad\qquad\qquad if \quad i \in A \\ v * \left\| \sum\limits_{i=1}^{n} P_i - (d_{DR} - P_{RES}) \right\|^2, \; if \quad i \in B \end{cases} \end{aligned} \tag{18}$$

where ω is the sum of the number of original agents and virtual agents, A is the number of original agents and B is the number of virtual agents.

It can be seen from Formula (18) that the original optimization model becomes a new unconstrained optimization model through the logarithmic barrier function and the virtual agent's processing of constraints. At the same time, the new unconstrained optimization model also contains some parameters for adjustment, where $t > 0$, $t^k = \mu t^{k-1}$ is the updated formula of parameter t, and $t^0 > 0, \mu > 1, v > 0$.

3.2. Fully Distributed ADMM Algorithm

Based on the above processing of the economic dispatch optimization model of the microgrid, a fully distributed ADMM algorithm based on logarithmic barrier function and virtual agent is proposed in this paper, which is presented as:

$$x_i^{k+1} = \underset{x}{argmin} f_i(x_i) + \sum_{j \in \mathcal{N}(i)} \left[\left(\lambda_{ji}^k - \lambda_{ji}^k \right)^T x_i + \rho \left\| x_j^k - x_i \right\|^2 \right] \tag{19}$$

$$\lambda_{ji}^{k+1} = \lambda_{ji}^k - \rho(x_j^k - x_i^{k+1}) \tag{20}$$

where $\mathcal{N}(i)$ is the set of agents adjacent to agent i.

Stopping criteria need to be introduced to make the proposed algorithm converge in finite time, which can improve the stability of the proposed algorithm in a closed loop. Similar to [16], the stopping criteria are designed according to two relationships: (1) the solution error between current agent and adjacent agent in each iteration; and (2) the solution error of current agent at time step k and $k-1$. The update of agents stops until the below stopping criteria are satisfied.

$$\begin{aligned} &\sum_{j \in \mathcal{N}_i} \left\| x_j^k - x_i^k \right\|_2 \leq \delta_i^{pri} \\ &\rho \left\| x_i^k - x_i^{k-1} \right\|_2 \leq \delta_i^{dual} \\ &\delta_i^{pri} = \delta^{abs} + \delta^{rel} \max_{j \in \mathcal{N}_i} \left\{ \left\| x_j^k \right\|_2, \left\| x_i^k \right\|_2 \right\}, \\ &\delta_i^{dual} = \delta^{abs} + \delta^{rel} \max_{j \in \mathcal{N}_i} \left\{ \left\| \lambda_{ji}^k \right\|_2 \right\} \end{aligned} \tag{21}$$

where δ_i^{pri} and δ_i^{dual} are primal error and dual error, respectively; and δ^{abs} and δ^{rel} are absolute and relative tolerances, usually chosen as 10^{-3} or 10^{-4} [16].

It can be seen from Formula (19) that the update of the variable, x_i, requires the value of the adjacent variable, x_j at the last moment, and it is independent of the value at the current moment, which has the characteristic of full distribution. Therefore, the ADMM algorithm in Formulas (19) and (20) only needs to communicate with adjacent agents, which decreases the computation and the communication burden. The algorithm is shown in Figure 2.

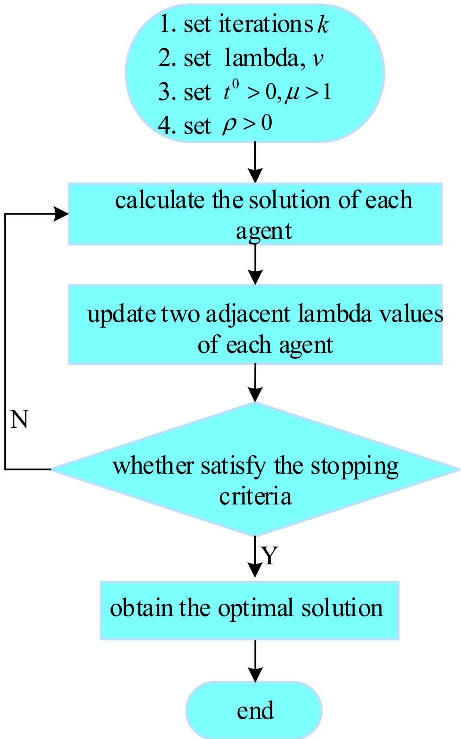

Figure 2. Flow chart of fully distributed ADMM algorithm.

3.3. Source-Load-Storage Collaborative Optimization Scheme

Based on the microgrid economic dispatch model with demand response proposed in Section 2 and the fully distributed ADMM algorithm proposed in Section 3.2, in this paper, we propose a two-layer source-load-storage collaborative optimization scheme that can realize fully distributed computing. The block diagram in Figure 3 is as follows.

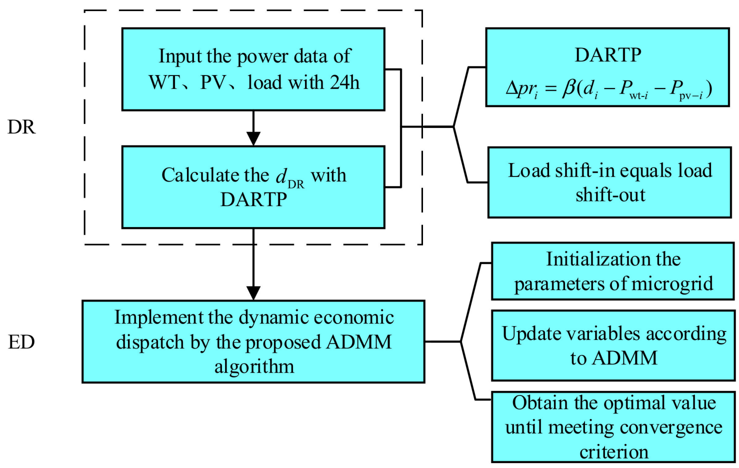

Figure 3. Block diagram of source-load-storage collaborative optimization.

Collaborative optimization is realized by the DR layer and the ED layer. The real-time load demand forest is implemented by utilizing the DAPRTP in the DR layer. Load shift-in equals load shift-out during the DR. In the ED layer, the fully distributed optimal allocation containing PV, WT, DG and ESS can be finished by employing the proposed ADMM algorithm. The optimization considers not only the power supply side but also the load demand side, which can enhance the consumption of the RESs as soon as possible and improve the interaction between generation and consumption.

4. Case Study

The proposed fully distributed ADMM algorithm is coded by Matlab, and the CVX algorithm package is used to simulate a 30-node microgrid system that consists of four DGs and two ESSs on a Windows 10 PC. The relevant parameters of the microgrid system are given in Table 1. The power profiles of WT, PV and load demand during a day (24 h) are shown in Figure 4. The single-time-slot economic dispatch and multiple-time-slot economic dispatch are implemented to verify the feasibility and effectiveness of the proposed approach.

Table 1. Parameters of simulation.

DERs	$a_i/(\$/MW^2h)$	$b_i/(\$/MWh)$	$c_i/(\$/h)$	P_i^{min}/MW	P_i^{max}/MW
DG_1	0.00375	2	0	0	200
DG_2	0.0175	1.75	0	0	200
DG_3	0.0625	1.0	0	0	80
DG_4	0.00834	3.25	0	0	200
ESS_1	0.025	3.0	0	−100	100
ESS_2	0.025	3.0	0	−100	100

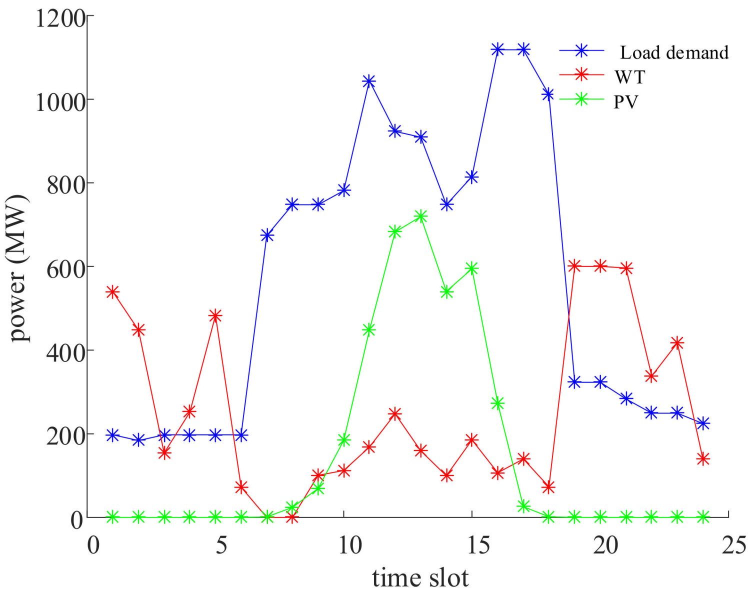

Figure 4. Power profiles of WT, PV and load demand.

4.1. Single-Time-Slot Economic Dispatch

4.1.1. Centralized ADMM for Single-Time-Slot Economic Dispatch

The centralized ADMM is the reference of power output, which is obtained with a traditional ADMM algorithm. The calculation result of centralized ADMM in the Table 2 is as follows.

Table 2. Centralized ADMM algorithm calculation results.

	DG_1	DG_2	DG_3	DG_4	ESS_1	ESS_2
P/MW	185.11	46.87	19.12	10.03	10.03	12.03
$f(P)$/MW			767.602			

4.1.2. Optimal Power Allocation of Fully Distributed ADMM Algorithm

When $p = 0.01$, $v = 100$, $t^0 = 0.01$ and $\mu = 2$, it can be clearly seen from Figure 5 that the final optimal solution of each DER basically fits the value obtained by the centralized algorithm in Table 2, which demonstrates the feasibility of proposed ADMM algorithm, and it converges to the optimal solution after only 143 iterations.

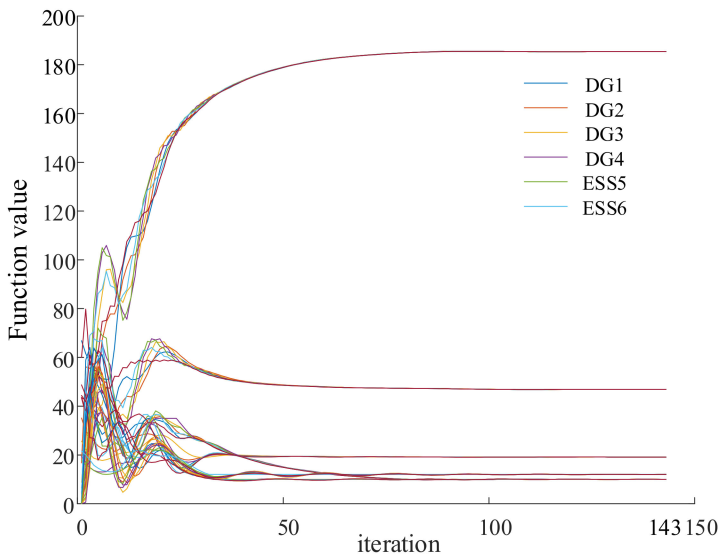

Figure 5. Optimal power configuration of the corresponding DER for each iteration.

In order to show that the proposed approach can converge to the global optima more clearly, Figure 6 shows the distances of the solution to the global optima from different perspectives. From the figures, we can see that: (1) the solution gradually approximates the global optima, and the error descends from 10^0 to 10^{-3} at time step k = 0–100; (2) the error stays between 10^{-3} and 10^{-4}, and the solution converges to the optima after time step $k > 100$, which illustrates that the convergence of the proposed approach can be guaranteed.

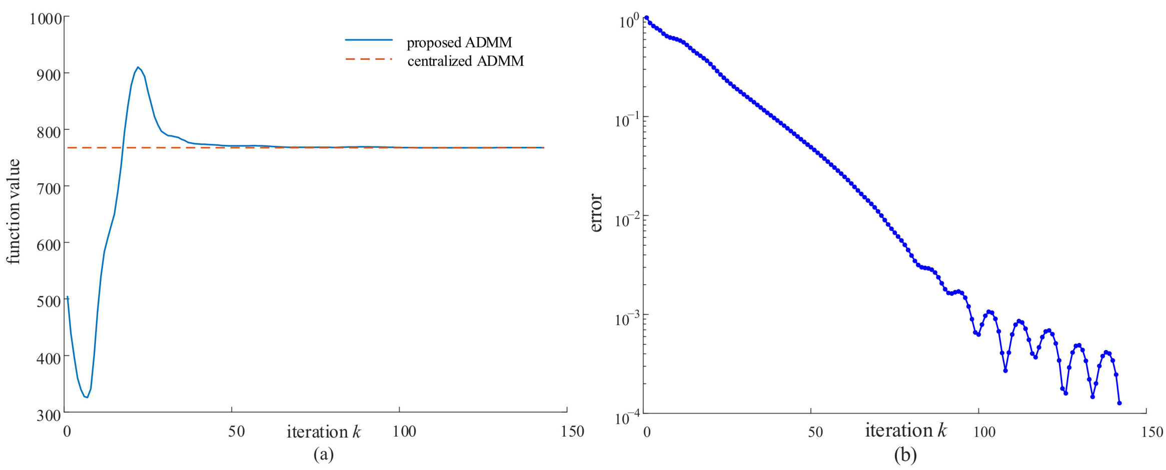

Figure 6. (**a**) Function value of the proposed ADMM and centralized ADMM. (**b**) The error between the solution of the proposed ADMM and the optima.

(1) The Influence of Parameters on The Convergence Speed of The Algorithm

It can be seen from Formula (18) that the optimization results of the objective function are closely related to the four variable parameters. Each parameter is analyzed one by one, and its influence on the optimization results of the algorithm is explored.

(1) parameter ρ

Here, μ = 2, v = 100 and t^0 = 0.01, keep μ, v, t^0 unchanged and change the value of ρ to explore its influence on the optimization result. Figure 7 is the comparison of the corresponding objective function values under different values of ρ. It can be seen from Figure 7 that the convergence rate is the fastest when ρ = 0.01, and the convergence rate is slower or even unable to converge when other ρ values are adopted.

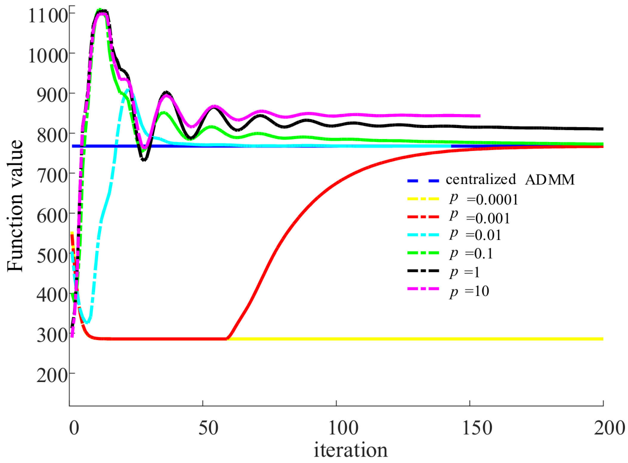

Figure 7. Influence of different ρ values on the value of the objective function.

(2) parameter v

Here, ρ = 0.01, μ = 2 and t^0 = 0.01, keep ρ, μ, t^0 unchanged and change the value of v to explore its influence on the optimization results (Figure 8). The influence of different values on the error of optimization results is the comparison of the errors obtained under different values of v. It can be seen from Figure 8, the influence of different values on the error of optimization results, that the convergence curve is almost the same when v = 100, 1000, or 10,000, indicating that the value at this time has little influence on the convergence speed, and when v = 0.1 or 0.01, it is difficult to ensure that the algorithm converges to the optimal solution, causing the speed of convergence to also lose its meaning.

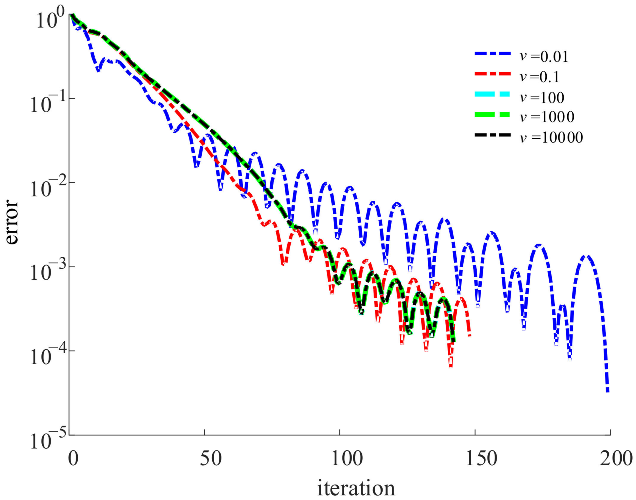

Figure 8. Influence of different v values on the error of optimization results.

(3) parameter μ

Here, $\rho = 0.01$, $v = 2$ and $t^0 = 0.01$, keep ρ, v, t^0 unchanged and change the value of μ to explore its impact on the optimization results. Figure 9, the influence of different values on the value of the objective function, is the comparison of the corresponding objective function values under different values of μ.

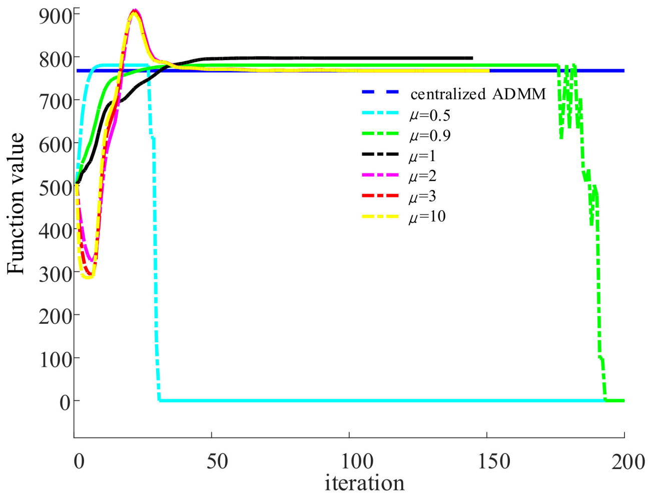

Figure 9. Influence of different μ values on the value of the objective function.

It can be seen from Figure 9, the influence of different values on the value of the objective function that when $\mu = 0.5$ or 0.9, that the objective function value deviates significantly from the reference function value and does not converge. When $\mu = 1$, although it can be converged, the objective function value is much higher than the reference function value and does not reach optimal levels. However, when $\mu = 2$, 3 or 10, the three objective function values fit the reference function value, and the curves almost overlap, indicating that the optimal solution has been reached.

(4) parameter t^0

Here, $\rho = 0.01$ and $v = 100$. It can be seen from the above that when $\mu > 1$, it is advisable to set $\mu = 2$, keep ρ, v, μ unchanged and change the initial value of t^0 to explore its influence on the optimization results. Figure 10 is the comparison of the corresponding errors under different values of t^0.

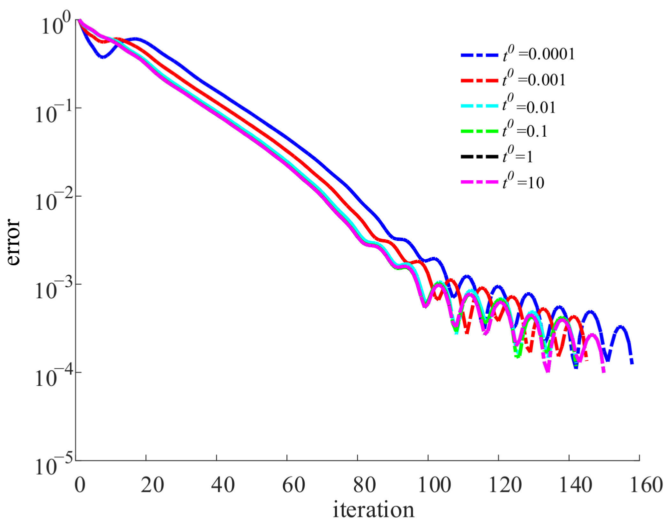

Figure 10. Influence of different t^0 values on the error of optimization results.

It can be seen from Figure 10 that the number of iterations is the most when t^0 = 0.0001, and the convergence speed is the slowest when t^0 = 0.001. The convergence speeds are fastest when t^0 = 0.01, 0.1, 1 or 10, and the optimal value can be reached after only 143 steps.

Some general conclusions can be obtained about the parameters of the proposed algorithm according to the sensitivity analysis. (1) The parameter ρ can search in the range of 0.0001–0.1, and the proper ρ is 0.01 for the proposed algorithm. (2) The parameter v can search when $v \geq 100$, and the proper v is 100 for the proposed algorithm. (3) The parameter μ can search when bigger than 1, and the proper μ is set as 2 for the proposed algorithm. (4) The parameter t^0 can search in the range of 0.01–10, and the proper t^0 is set as 0.01 for the proposed algorithm. Convergence can be guaranteed under these conditions.

(2) The Influence of the Number of Virtual Agents on the Optimization Results

In Formula (16), B is the number of virtual agents. Different choices of B also change the optimization results. The following selects different numbers of B to explore its specific impact on the optimization results. Figure 11 reflects that the smaller the number of virtual agents is, the better the convergence speed is.

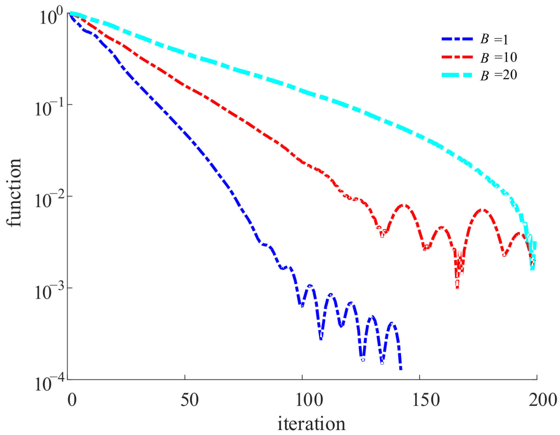

Figure 11. Influence of different B values on the optimization result error.

(3) Test of Plug-and-Play Capability

Plug-and-play capability is tested to demonstrate the flexibility of the microgrid system. Without loss of generality, the DER6 is plugged out at time step k = 100 due to faults and plugged in at time step k = 170 due to recovery. The cost function can converge to the optimal value whenever DER6 is plugged out or in, as shown in Figure 12a. Each DER reallocates the power output to a new steady state when the DER6 is plugged out and recovers the original optimal value when the DER6 is plugged in, as shown in Figure 12b. Thus, the proposed ADMM algorithm can still be effective for the case of plug and play.

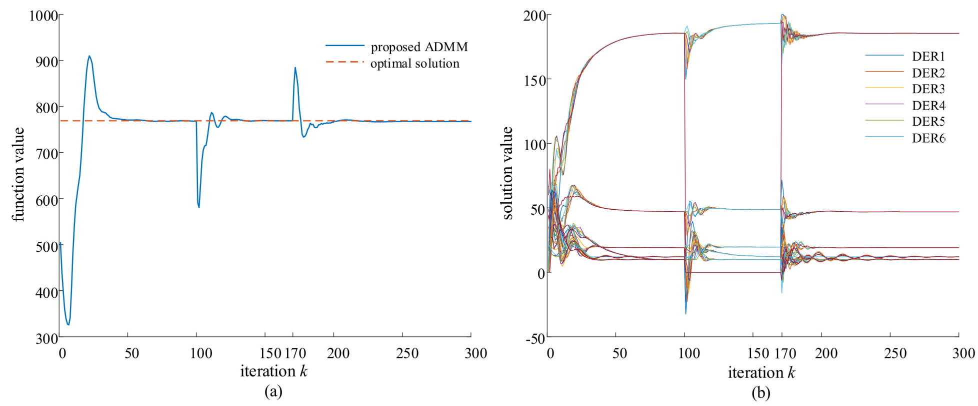

Figure 12. (**a**) Value of the cost function under the plug-and-play test. (**b**) Value of each DER under the plug-and-play test.

4.2. Multiple-Time-Slot Economic Dispatch

Collaborative Optimization Results with Real Time Demand Response

Figure 13 is a comparison diagram of the load before and after the demand response, and Figure 14 is a comparison diagram of the electricity price before and after the demand response. Combining Figures 13 and 14, it can be seen that the peak periods of the difference between the load demand and the sum of the WT and PV power output are at 07:00–09:00 and 16:00–18:00. The load adjustment is obvious during the time slots while realizing the purpose of shifting the load from more to less under the high electricity price. The periods of 01:00–05:00 and 20:00–23:00 are the valley periods of the difference between the load demand and the sum of the WT and PV power output. At this time, the load only needs to be adjusted slightly to meet the scheduling requirements.

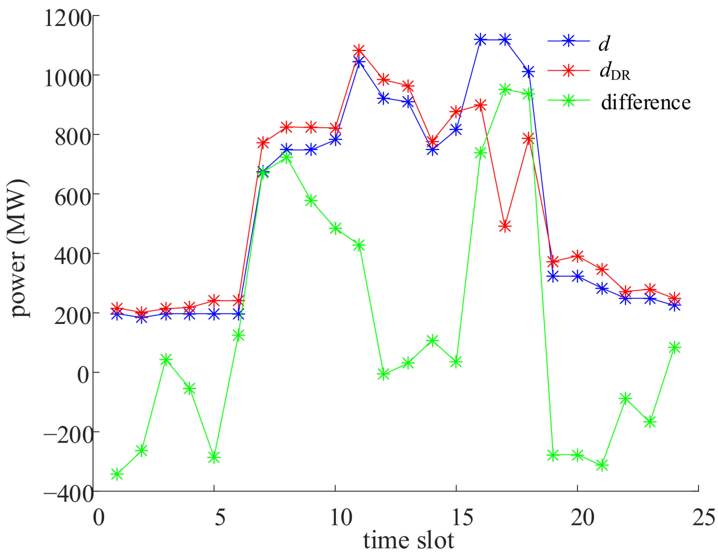

Figure 13. Comparison of load demand before and after demand response.

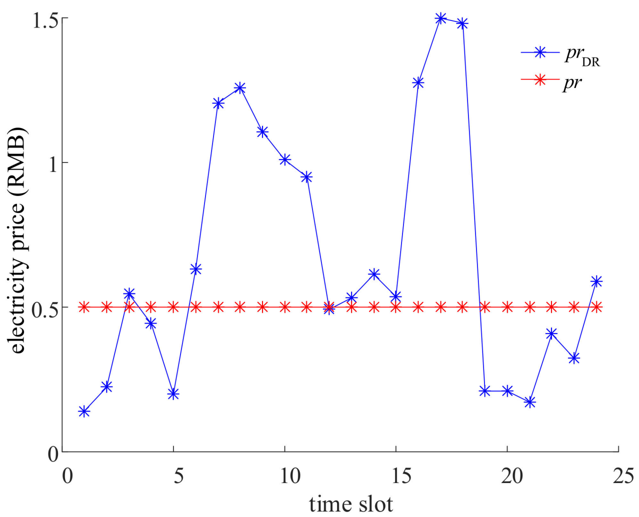

Figure 14. Changes in electricity prices before and after demand response.

The coordination optimization results of DERs with the demand response are shown in Figure 15. It can be seen from the figure that when the load demand is less than the sum of the WT and PV power generation, the excess power is used for energy storage charging, and other distributed power sources are no effort required. When the load demand is greater than the sum of the WT and PV power generation, at this time, in addition to the power output of the distributed power generation, energy storage is needed to ensure the balance between supply and demand by discharging.

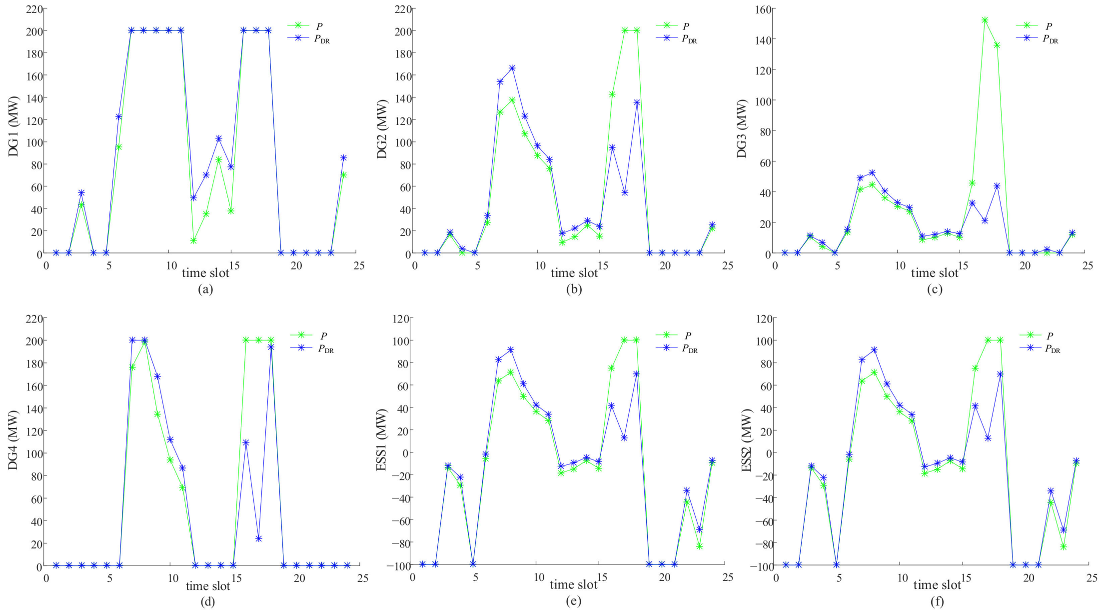

Figure 15. (**a**) Power output of DG 1. (**b**) Power output of DG 2. (**c**) Power output of DG 3. (**d**) Power output of DG 4. (**e**) Power output of ESS 1. (**f**) Power output of ESS 2.

5. Conclusions

Aiming at the distributed demand of microgrid economic dispatch, in this paper, we propose a fully distributed ADMM algorithm based on the logarithmic barrier function method and virtual agent and apply them to microgrid economic dispatch. In addition, a demand response based on the real-time electricity price is introduced into the economic dispatch of the microgrid. Thus, a source-load-storage energy microgrid optimization scheme is proposed. The economic scheduling method has the following characteristics. (1) the constraint conditions are processed by the logarithmic barrier function method and virtual agent, which greatly reduces the computational complexity and simplifies the implementation steps by adding the inequality constraint to the objective function and setting proper virtual agents for equality constraint. (2) Compared to other distributed ADMM algorithms, which can be called fully distributed algorithms outwardly and still need a coordination center to collect information of each agent, the proposed algorithm is a fully distributed calculation and requires no coordination center and only needs limited information exchange with two adjacent distributed power sources to configure the optimal power of the dispatchable distributed power sources. (3) The proposed source-load-storage coordination scheme realizes dynamic economic dispatch with demand response by introducing the RTP, which not only improves the utilization efficiency of RESs but also takes user behavior into consideration to form a bidirectional feedback dispatchable scheme.

This paper currently only considers the power constraints of DERs in the economic dispatch optimization model and ignores the uncertainty of power output of PV and WT. Thus, the other constraints, such as line constraints and the uncertainty of RESs, will be considered in the optimization model, which is the future research direction to improve the accuracy, reliability and scope of application of the optimization model.

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