Distributed Optimization Scheduling Consistency Algorithm for Smart Grid and its Application in Cost Control of Power Grid

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***Abstract*—There are problems such as low scalability and low convergence accuracy in the economic dispatch of smart grids. To address these situations, this study considers various constraints such as supply-demand balance constraints, climb constraints, and capacity constraints based on the unified consensus algorithm of multi-agent systems. By using Lagrange duality theory and internal penalty function method, the optimization of smart grid economic dispatch is transformed into an unconstrained optimization problem, and a distributed second-order consistency algorithm is proposed to solve the model problem. IEEE6 bus system testing showed that the generator cost of the distributed second-order consistency algorithm in the first, second, and third time periods was 2.2475 million yuan, 5.8236 million yuan, and 3.7932 million yuan, respectively. Compared to the first-order consistency algorithm, the generator cost during the corresponding time period has increased by 10.23%, 11.36%, and 13.36%. The actual total output has reached supply-demand balance in a short period of time with the changes in renewable energy, while maintaining supply-demand balance during the scheduling process. The actual total output during low, peak, and off peak periods was 99MW, 147MW, and 120MW, respectively. This study uses distributed second-order consistency algorithm to solve the economic dispatch model of smart grid to achieve higher convergence accuracy and speed. The study is limited by the assumption that the cost functions of each power generation unit are quadratic convex cost functions under ideal conditions. This economic dispatch model may not accurately reflect practical applications.**

***Keywords*—Distributed consistency algorithm; convex optimization; economic dispatch; smart grid**

I. Introduction

In the context of rapid climate change and the crisis of non-renewable energy, traditional power grids have faced enormous challenges, such as low stability, strong concentration, and poor coordination of the power system. Therefore, the development of smart grids is urgent, and their advantages are as follows: they can achieve bidirectional flow of electricity and information, are suitable for different types of storage facilities and power generation equipment, and can automatically detect and repair system faults. Under the goal of ensuring stability, economy, and sustainability, smart grids are developing towards a more environmentally friendly, economical, safe, and efficient direction. The economic dispatch of smart grids (EDoSG) is a process that considers multiple constraints to ensure the overall stability, safety, and economic operation of the system. Its essence is a multi-objective optimization problem. Studying EDoSG under the dual carbon target has positive significance [1-3]. With the complexity of smart grid network structure and the increase in grid scale, EDoSG has encountered significant obstacles. For example, in practical situations, factors such as energy storage devices (ESD) and renewable energy are complex and variable, and the accuracy of model solving algorithms is low. Centralized power grid economic dispatch has poor scalability, low flexibility, and low robustness, while distributed economic dispatch (DED) can achieve plug and play of power sources, avoiding the drawbacks of the former [4-5]. At the same time, the consistency theory of multi-agent systems (MAS) has been recognized by economic dispatch researchers due to its own characteristics [6-7]. In response to various constraints such as supply-demand balance (SDB) constraints, climb constraints, and capacity constraints in EDoSG optimization problems, this study will transform the optimization problem into an unconstrained optimization problem through Lagrange duality theory (LDT) and internal penalty function method (IPFM). Additionally, it combines with the consistency algorithm to design a distributed second-order consistency algorithm (D2OCA), aiming to improve the operational accuracy and convergence effect of the solving algorithm, and thereby reduce the cost of smart grids. As one of the fundamental issues in the operation of smart grids, the economic dispatch problem of smart grids is studied. A more practical smart grid economic dispatch model is considered for distributed dispatch analysis. Intelligent economic dispatch with energy storage devices and renewable energy under complex constraint conditions has outstanding advantages in practical applications. The advantages of the research are as follows: Based on the D2OCA, a consistency algorithm that can be used to solve economic scheduling problems considering generators, energy storage units (ESU), and renewable energy is proposed. The convergence performance of the proposed algorithm is verified through simulation comparison with traditional consistency algorithms. The constructed economic dispatch model achieves collaborative optimization by exchanging information with adjacent units and making autonomous decisions to adjust its own output in the communication network. The technology proposed in the study can always meet the SDB constraints and the capacity constraints of each power generation unit during the scheduling process, and can converge to the optimal solution in a relatively fast time. This scheduling method has advantages such as strong scalability, information confidentiality and security, and robustness. It is of great significance in the fields of smart grid economy, stability, and safe operation. This study elaborates on the content from the following four sections. Section I analyzes the current situation of centralized EDoSG and smart grid DED both domestically and internationally. Section II focuses on the first-order consistency algorithm (1OCA) and D2OCA in EDoSG problems. Section III analyzes the convergence performance and accuracy of D2OCA. Section IV summarizes the research results and elaborates on the limitations and shortcomings of the study.

II. Related Works

Against the backdrop of the continuous development of new energy technologies, scholars in the field of smart grids have conducted extensive research on economic low-carbon scheduling. Guo R et al. established a stepped carbon trading model with different carbon emission ranges corresponding to different carbon trading prices. The goal of this model was to minimize the sum of power generation costs and carbon emissions, while considering safety constraints. Case studies have shown that analyzing the tiered carbon trading mechanism (TCTM) has great advantages in guiding the operation of low-carbon economy (LCE) in the system, providing necessary support for the LCE operation of smart grids [8]. Cui D's teams have proposed a peak shaving and valley filling model to regulate the LCE clean power system. It could preliminarily achieve LCE scheduling of integrated energy systems [9]. Scholars such as Zhu X have established an LCE scheduling model under TCTM, focusing on electrical and thermal integrated energy systems. Through comparative analysis of multiple scenarios, the proposed technology improved the economic benefits of the system by consuming wind power, thereby reducing the cost of the power grid [10]. Fu Y and researchers proposed a DED scheme that combines consensus theory and deep strong zeroing learning theory to solve the problems of low security and scheduling effectiveness of centralized algorithms in the optimization scheduling of smart grids. This scheme used Adam algorithm and consistency algorithm to obtain the optimal economic scheduling of unit output. This scheme was suitable for smart grids with complex network structures and could handle economic dispatch problems with large-scale data, reducing the impact of the objective function on economic dispatch results [11].

Ayalew F et al. summarized relevant literature reports on existing economic dispatch problems in smart grids, including economic dispatch, centralized and distributed algorithms, demand side management, etc. [12]. Ismi et al. analyzed the economic dispatch problem under assumed uncertainty and solved it through centralized methods under load or energy changes to maintain the stability of the power system [13]. Wang et al. proposed an economic scheduling algorithm for parallel computing in distributed power nodes, which has higher convergence performance compared to centralized methods [14]. Sadouni H et al. analyzed the current research status of smart grid DED problems, including efficient uninitialized processes, distributed power generation systems with practical constraints, and safety [15]. Liu H et al. proposed a finite time DED model suitable for smart grids. The simulation results obtained through DED algorithm had high robustness in time-varying communication networks [16]. Table I refers to the limitations of the relevant research work.

TABLE I. LIMITATIONS OF RELATED RESEARCH WORK

Reference	Achievement	Limit
Guo R [8]	Established a tiered carbon trading model with different carbon emission ranges corresponding to different carbon trading prices	Only considering carbon constraints and emissions
Cui D [9]	Proposed a peak shaving and valley filling model to regulate the economic, low-carbon, and clean power system	The applicability of scheduling models is limited
Zhu X [10]	Established a low-carbon economic dispatch model under a TCTM	Mainly aimed at minimizing economic operating costs
Fu Y [11]	Obtained the optimal economic dispatch of unit output through Adam algorithm and consistency algorithm	DED not considered
Ayalew F [12]	Analyzed relevant literature on existing economic dispatch problems, including economic dispatch, centralized and distributed algorithms, demand side management, etc.	No mention of D2OCA
Ismi [13]	Solved economic dispatch under load or energy changes through centralized methods	There are too many assumptions in the model
Wang S [14]	Proposed an economic scheduling algorithm for parallel computing in distributed power generation nodes, which has high convergence performance	But compared to the latest scheduling algorithms, the convergence performance is average
Sadouni H [15]	Analyzed the current situation of distributed power generation systems	Failure to analyze the algorithm for solving the DED model of the smart grid
Liu H [16]	Distributed economic scheduling algorithms have extremely high robustness in time-varying communication networks	Model solving without considering consistency algorithms

Based on the current situation of centralized smart grid and DED, current consistency algorithms have a positive role in EDoSG optimization problems, but EDoSG also has prominent problems. In economic dispatch, few scholars analyze energy storage equipment, renewable energy, and power generation constraints. Based on this, this study proposes D2OCA to achieve EDoSG on the basis of multi-agent consensus algorithms, providing new development directions for the sustainable development of smart grids.

III. EDoSG Model of D2OCA

The goal of EDoSG is to find the optimal power generation with the minimum economic cost while ensuring that the system constraints are met. The economic scheduling method commonly used in the past for generator scheduling was centralized, but the optimal scheduling solution obtained from this method cannot meet the real-time requirements of distributed power consumption and power outage. DED has advantages such as simple protocol, strong scalability, and low complexity, which can achieve safe and stable economic operation of smart grids. The study examines different limitations, including SDB and climb constraints. Using the unified consensus algorithm of multiple intelligent systems, it transforms the optimization problem of smart grid economic dispatch into an unconstrained optimization problem through LDT, IPFM, and the alternating direction multiplier method (ADMM). At the same time, a D2OCA is proposed to solve the optimization model problem of smart grid economic dispatch.

A. EDoSG and Multi-Intelligent 1OCA

The research content of DED problem in smart grid is to maximize the economic effect of power generation under the constraint of power generation unit, that is, to find the optimal power generation required at the lowest cost. The research on DED problems can be divided into three parts: problem modeling, algorithm design, algorithm analysis, and validation [17-18]. Problem modeling is a convex optimization problem, but it involves constraints such as SDB and capacity constraints in economic scheduling problems. Therefore, this study utilizes IPFM to remove capacity constraints, while utilizing LDT to address SDB constraints and climb constraints. If the set is a convex set, then all points on the line connecting any two points x_1 and x_2 in set $C \in R^n$ are in set C, then it can be considered a convex set, that is, Eq. (1).

$$\beta x_1 + (1-\beta) x_2 \in C \quad (1)$$

In Eq. (1), β refers to any real number within 0-1, and the convex function (CF) f of C on the convex set must satisfy Eq. (2).

$$f\left(\beta x_1 + (1-\beta) x_2\right) \le \beta f(x_1) + (1-\beta) f(x_2) \quad (2)$$

When the coordinates of points x_1 and x_2 are the same. Eq. (2) takes equal sign. At this point, f is a strictly CF on the convex set C. The optimization problem with constraints can be referred to by Eq. (3).

$$\min_x f(x) \quad s.t. g_i(x) \le 0, h_j(x) \le 0 \quad (3)$$

In Eq. (3), $f(x)$ and $g_i(x)$ are different CFs, $h_j(x)$ is an affine function, $i = 1, \cdots, n$, $m = 1, \cdots, m$, $j = 1, \cdots, j$. Fig. 1(a) is a schematic diagram of a CF.

The methods for solving convex optimization problems include Newton's method, Lagrangian dual function method, IPFM, etc. The solving principle of IPFM is shown in Fig. 1 (b). IPFM converts constraint conditions into obstacle terms that constrain the objective, and the iteration point needs to be far away from the boundary of the feasible domain to find the optimal solution. When the iteration point approaches the boundary of the feasible domain, the value of the obstacle term tends to infinity. The augmented objective function $L(x, \gamma)$ constructed by this method is represented by Eq. (4).

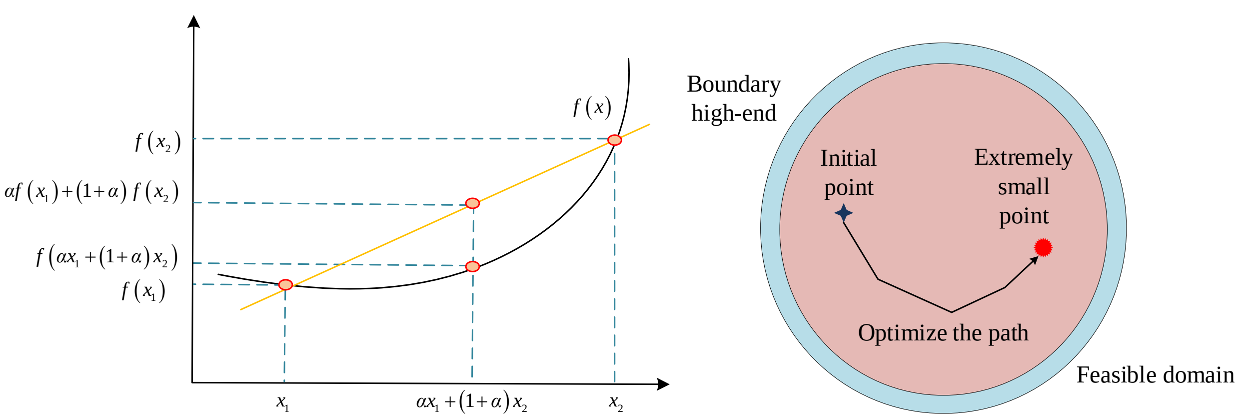
$$L(x, \gamma) = f(x) + \gamma b(x) \quad (4)$$

In Eq. (4), the penalty factor is γ. To reduce the impact of this parameter on the function value, it is defined as a first-order jump function, and the value increases with time. The obstacle function is $b(x)$, characterized by continuous numerical values within the feasible domain. If the constraint conditions are met, its numerical value is a finite positive number. LDT is suitable for raw optimization problems that are difficult to handle. A generalized Lagrangian function based on Eq. (3) is built and the Eq. (5) is used to refer to it.

$$L(x, a, b) = f(x) + \sum_{i=1}^{n} a_i g_i(x) + \sum_{j=1}^{m} b_j h_j(x) \quad (5)$$

In Eq. (5), the Lagrange multiplier is represented by b, and the dual variable is a. The dual problem of the original problem can be represented by Eq. (6).

$$\max_{a,b,a_i \ge 0} L_D(a, b) = \max_{a,b,a_i \ge 0} \min_x L(x, a, b) \quad (6)$$



(a) Schematic diagram of convex functions

(b) The Principle of Solving Internal Penalty Function Method

Fig. 1. The schematic diagram of CFs and the principle of solving IPFM.

In Eq. (6), $D=\{x\in R^n : k_i(x)\geq 0\}$ refers to the feasible region and $k_i(x)$ refers to the boundary function of the feasible region. The optimal solutions for the original problem and the dual problem are p^* and d^*, respectively, as shown in Eq. (7).

$$d^* = \max_{a,b,a_i\geq 0} \min_{x} L(x,a,b) \leq \min_{x} \max_{a,b,a_i\geq 0} L(x,a,b) = p^* \quad (7)$$

The ADMM, as an extension of augmented Lagrangian, is a framework for solving large-scale data in machine learning. It can transform large-scale image problems into relatively simple local sub-problems, and obtain global solutions by calculating the solutions of local sub-problems. ADMM solves constrained local problems by introducing auxiliary variables, decomposing the objective function containing the original problem into multiple easily solvable local sub-problems. ADMM is related to iterative algorithms such as splitting, multiplier methods, and dual decomposition methods, and is very suitable for solving distributed convex optimization problems. On the basis of augmenting the Lagrangian function, ADMM has multiple advantages in simplicity, efficiency, and convex optimization solving. It can solve the minimization problem with equality constraints on two variables and the objective function, as shown in Eq. (8).

$$\min_{x,z} \ f(x)+g(z) \quad s.t. Wx+Bz=c \quad (8)$$

In Eq. (8), x, z, and c refer to vectors, W, and B matrices. x and z are the optimization variables for the demand solution. $f(x)+g(z)$ refers to minimizing the objective function, which can be composed of the function of variable x and z. They can handle regularization terms in optimization objectives of statistical learning problems, consisting of equality constraints. The specific process of minimizing iterative solutions and updates is as follows. Combining the linear part with the quadratic term yields a concise scaling form, with the specific iteration process as follows. One is to calculate and minimize related problems, and solve variables. The second is the calculation and related minimization problem. The third is to update the dual variables until the algorithm reaches the convergence condition. The multiplier method in ADMM refers to the dual ascent method of augmented Lagrangian functions, while the alternating direction refers to the alternating updates between the original variable and the dual variable. Fig. 2 is a schematic diagram of ADMM.

B. EDoSG Combined with D2OCA

The EDoSG problem considers ESDs, renewable energy, and generators, due to differences in ideal models and power generation equipment. Therefore, the generator set needs to consider capacity constraints, climb constraints, and SDB on both sides, and based on this, construct D2OCA to solve the EDoSG problem. The MAS is a system that places individual agents to achieve overall optimization goals. According to different control strategies, MASs can be divided into three structural systems: hybrid, distributed, and centralized [19-20]. Fig. 3 is a diagram of a distributed system.

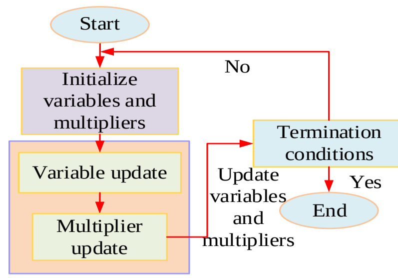


Fig. 2. Schematic diagram of alternating direction multiplier method.

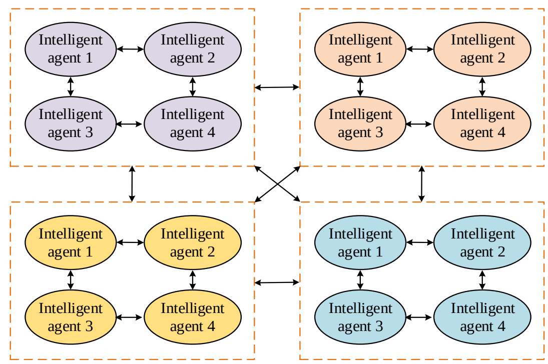


Fig. 3. Schematic diagram of a distributed system.

In a distributed architecture system, the task of each agent is to collect local information, exchange and update information with neighboring agents, with the aim of achieving task objectives. The consistency problem of MASs has been applied in EDoSG and state estimation of power networks, which can be described through graph theory. The communication topology relationships of various generator units in EDoSG can be represented through graph theory. Fig. 4(a) and 4(b) are directed and undirected graphs, respectively. The difference between the two graphs is that directed graphs have directions, while undirected graphs have no directions.

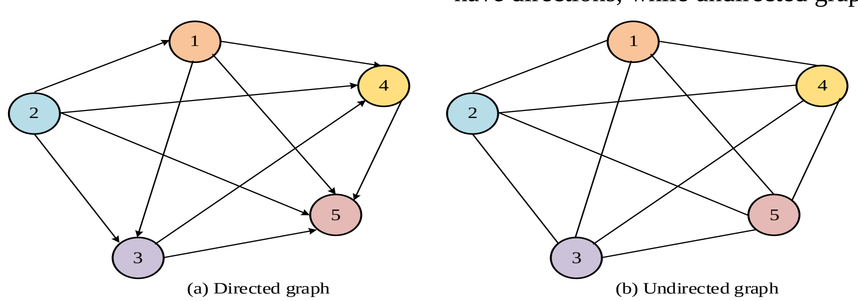


Fig. 4. Schematic diagrams of directed and undirected graphs.

The topology of multi-agent networks is represented by an undirected graph $G=(V,E,A)$. The state information of the i-th agent in a MAS at time t is $x_i(t)$. The model of a MAS with first-order continuous time is Eq. (9).

$$\overline{x}_i(t)=u_i(t) \tag{9}$$

In Eq. (9), the control input at time t is $u_i(t)$. The classic 1OCA under continuous time is expressed as Eq. (10).

$$\overline{x}_i(t)=u_i(t)=\sum_{j=1}^{n}a_{ij}\left(x_j(t)-x_i(t)\right) \tag{10}$$

The matrix form of Eq. (10) indicates that the states of each agent gradually reach homogeneity, i.e. $x_j(t)-x_i(t)\to 0$. The first-order consistent dynamic model of MASs in discrete-time is Eq. (11).

$$x_i(k+1)=x_i(k)+u_i(k) \tag{11}$$

The distributed consistency algorithm achieves the same value of state variables through a consistency mechanism, including average consistency, arithmetic consistency, geometric consistency, and harmonic consistency. The daily economic dispatch period can be divided into flat peak, low valley, and peak. The total demand during the corresponding time period is 128MW, 96MW, and 148MW, respectively. The total output of ESU and renewable energy is 20MW, 10MW, and 13MW, respectively. Eq. (12) is the mathematical expression for the EDoSG problem.

$$\begin{cases} \min\sum_{h=1}^{H}\sum_{i=1}^{N}\left(f_{i.h}(P_{i,h})+g_{i,h}(S_{i,h})\right) \\ \sum_{i=1}^{N}\left(P_{i,h}+R_{i,h}+S_{i,h}\right)=D_h \\ -P_i^R\le P_{i,h}-P_{i,h-1}\le P_i^R \\ P_i^m\le P_{i,h}\le P_i^M \\ S_i^m\le S_{i,h}\le S_i^M \end{cases} \tag{12}$$

In Eq. (12), the different time periods in the daily schedule are $h=[1,2,\cdots,H]$. The output power of the i-th generator during time period h is $P_{i,h}$. The output power of the i-th ESU is $S_{i,h}$. The output power of the i-th renewable power generation unit is $R_{i,h}$. The expected electricity demand during time period h is D_h. The ramp rate limit for the i-th generator is P_i^R. The min-output and max-output of the i-th generator are P_i^m and P_i^M, respectively. The min-output and max-output of the i-th ESU are S_i^m and S_i^M, respectively. The cost functions for the i-th ESD and the i-th generator during time period h are $g_{i,h}(S_{i,h})$ and $f_{i.h}(P_{i,h})$, respectively, and the calculation formula is Eq. (13).

$$\begin{cases} f_{i.h}(P_{i,h})=a1_{i,h}P_{i,h}^2+a2_{i,h}P_{i,h}+a3_{i,h} \\ g_{i,h}(S_{i,h})=b1_{i,h}S_{i,h}^2+b2_{i,h}S_{i,h}+b3_{i,h} \end{cases} \tag{13}$$

In Eq. (13), the cost parameters of the generator cost function are $a1_{i,h}$, $a2_{i,h}$, and $a3_{i,h}$, and the cost parameters of the ESU cost function are $b1_{i,h}$, $b2_{i,h}$, and $b3_{i,h}$. Table II shows the cost parameters of the generator in the communication topology diagram of three nodes. Each vertex in the communication topology diagram is connected to a generator, ESD, renewable energy, $i=3$, $h=3$. The Laplace matrix can be expressed as $W=\begin{bmatrix}2 & -1 & -1\\ -1 & 2 & -1\\ -1 & -1 & 2\end{bmatrix}$.

TABLE II. COST PARAMETERS OF GENERATORS IN THE COMMUNICATION TOPOLOGY DIAGRAM OF THREE NODES

Alternator	$a1$	$a2$	$a3$	P^m	P^M	P^R
$P_{1,1},P_{1,2},P_{1,3}$	0.0075	-1	0	34	78	28
$P_{2,1},P_{2,2},P_{2,3}$	0.2500	-4	0	9	32	17
$P_{3,1},P_{3,2},P_{3,3}$	0.1000	2	0	17	49	18

Before solving the optimal solution, the EDoSG model needs to propose the following assumptions: the communication topology of the smart grid is connected and undirected, and the capacity constraints of the generator and ESU can be found internally. The direct solution of the EDoSG model is computationally challenging, and research is needed to transform the problem into an unconstrained optimization problem before solving it. Based on the assumptions and IPFM, the EDoSG problem can be described again using Eq. (14).

$$\begin{cases} \min\sum_{h=1}^{H}\sum_{i=1}^{N}\left(f^{\gamma}_{i,h}(P_{i,h})+g^{\lambda}_{i,h}(S_{i,h})\right) \\ \sum_{i=1}^{N}\left(P_{i,h}+R_{i,h}+S_{i,h}\right)=D_h \\ -P_i^R\le P_{i,h}-P_{i,h-1}\le P_i^R \end{cases} \tag{14}$$

According to LDT, the EDoSG problem can be transformed into an optimal solution of $(P^*,S^*,\mu^*,\lambda^*)$. Renewable energy has characteristics such as intermittency, volatility, and randomness, making it difficult for smart grids to control output power. To ensure the stability of the renewable energy generation grid, the smart grid is set to maintain a fixed value of renewable energy and ESUs through the output of ESUs during the time period, and the SDB can be regarded as unchanged. Based on assumptions and the expression of D2OCA, this study proposes D2OCA in the EDoSG problem. The new variables for P_i and S_i in this method are B_i and U_i, respectively, and the convergence parameters are η_P and η_S. This D2OCA has high convergence performance, which can be confirmed by the research conclusions of scholars in the supply and demand balance of smart grids. The ESU does not change with the fluctuation of renewable energy supply at the beginning of each time slot, but it can still reach the optimal solution through the convergence process within each time slot.

IV. Analysis of D2OCA Simulation Results in EDoSG

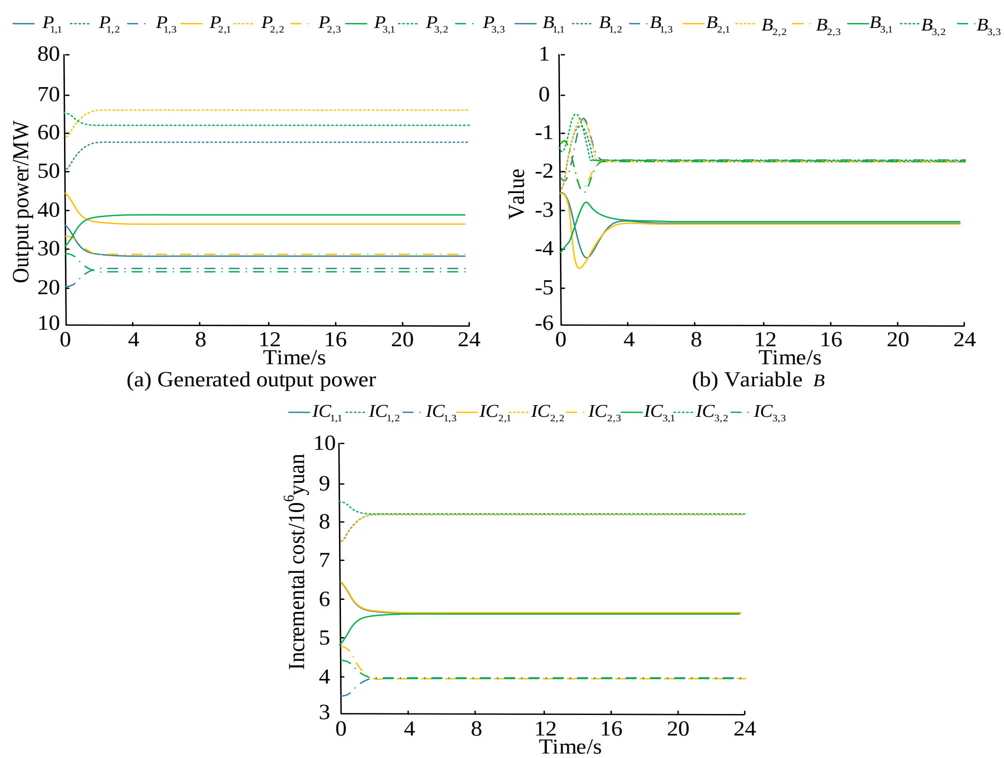
The performance of the D2OCA for smart grids is analyzed, including convergence performance and output power. The used testing system is the IEEE6 bus system, and the communication topology of the smart grid is represented by an undirected graph with three vertices. The cost function of generators and energy storage can be represented by a quadratic function. The classic economic scheduling algorithm, 1OCA, is known for its ideal convergence accuracy and speed. The D2OCA, optimized from 1OCA, is used as a comparative algorithm. Both algorithms are reasonable. The operating system is Windows 7, the storage is solid-state drives, the central processing unit is Intel Core i7, and the operating memory is 16GB. Table III shows the power generation cost parameters of the ESU. The time slot is set to 24 seconds, and the starting output power of the generator is (47, 15, 25, 72, 28, 31, 50, 23, 35) MW. The starting output power of the ESU is (5, 3, 3, 6, 3, 4, 8, 8, 4) MW. The initial values of B_i and U_i are 0, and the η_P values during low, peak, and off peak periods are 2.54, 3.95, and 2.20, respectively. The η_S value for all three time periods is 2.14, and the initial values for a and b are all 10.

This study first conducts economic dispatch simulation analysis on the output power of the generator and variable B_i. Fig. 5(a) to 5(c) show the economic dispatch results of the output power P_i, variable B_i, and incremental cost IC_i of the smart grid D2OCA. In Fig. 5(a), different generators can converge to stable values in a short period of time at different time periods. The output power of each generator during low, peak, and off peak periods is consistent with the actual electricity consumption. There are significant differences in the output power of different generators. In Fig. 5(b), the stable values of variable B_i for different generators during the same time period are the same, which are (-2.3816, -2.3715, -3.5029). In Fig. 5(c), the incremental cost of the generator gradually converges with the output power, and the incremental cost of power generation during the low, peak, and flat peak periods is consistent, with values of 6.0874, 9.4528, and 7.7068, respectively.

TABLE III. Power Generation Cost Parameters of Energy Storage Units

Energy storage unit	$b1$	$b2$	$b3$	S^m	S^M
$S_{1,1}, S_{1,2}, S_{1,3}$	0.7	-1	0	0	30
$S_{2,1}, S_{2,2}, S_{2,3}$	0.5	-2	0	0	20
$P_{3,1}, P_{3,2}, P_{3,3}$	0.2	1	0	0	20

Fig. 6(a) to 6(b) respectively refer to the iterative results of variables a and b. Both variables a and b converge to a value of 0 in a relatively short period of time. The convergence speed during low valley periods is moderate, the convergence speed during peak periods is the slowest, and the convergence speed during off peak periods is the fastest. Based on Fig. 5, when the two variables a and b reach convergence values, the output power of the generator gradually tends towards the optimal economic dispatch result.

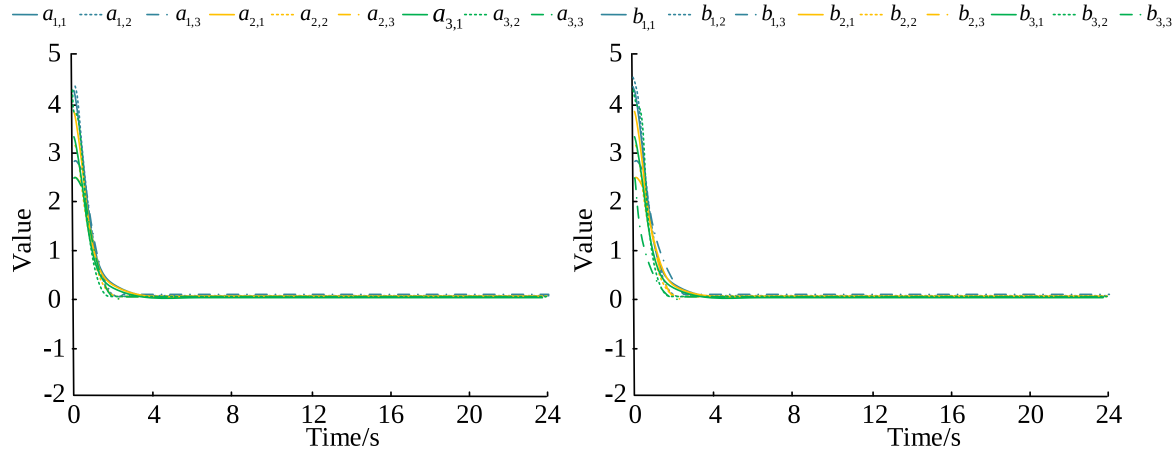


(a) Generated output power

(b) Variable B

(c) Incremental cost

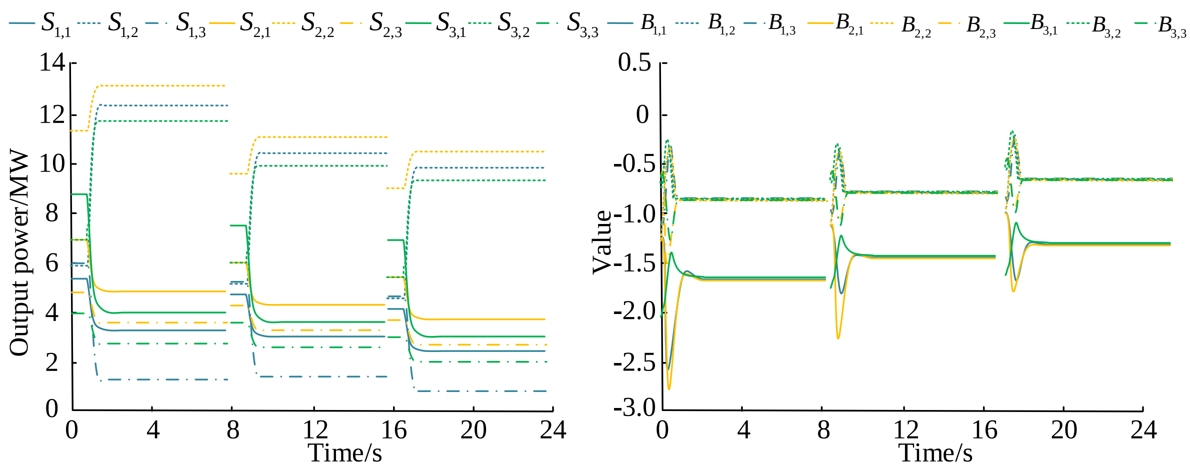
Fig. 5. Economic dispatch results of D2OCA for smart grid.



(a) Variable a (b) Variable b

Fig. 6. Iteration results of two variables.

This study then conducts economic dispatch simulation analysis on the output power and variable U_i of the ESU. Fig. 7(a) and 7(b) respectively refer to the optimal scheduling results of the output power and variables of the ESU. In Fig. 7 (a), at the beginning of each gap, the output of renewable energy leads to the output power of the ESU, and reaches the optimal value at each time slot. There is no significant variation pattern between the output power of the ESU and the electricity consumption period and the type of ESU. The optimal scheduling results for ESUs in the first time slot are (0.747, 2.0424, 5.2028, 0.8419, 2.1896, 5.9849, 1.5867, 3.2635, 10.968). In the second time slot, the optimal scheduling result of the ESU decreases, with values of (0.6279, 1.8568, 4.4679, 0.7356, 2.0356, 5.2132, 1.3758, 2.8965, 9.5689). When the time increases to the third time slot, the optimal scheduling result of the ESU is lower than that of the second gap, but the magnitude of the decrease does not show a clear pattern of change. In Fig. 7(b), the variable U_i for each time slot reaches a convergence value. As the time slot increases, the numerical value of convergence also gradually increases. In the third time slot, the convergence values of variable U_i are (0.1087, 0.1087, 0.1185, -0.1582, -0.1582, -0.1583, -0.3660, -0.3659, -0.3660).



(a) Energy storage unit output power (b) Variable B

Fig. 7. Optimal scheduling results for output power and variables of ESUs.

Fig. 8 shows the simulation results of the actual total output at different time periods. The actual total output reaches SDB in a short period of time with changes in renewable energy, while remaining in SDB during the scheduling process. The actual total output during low, peak, and off peak periods is 99MW, 147MW, and 120MW, respectively.

Finally, this study validates the results of D2OCA in EDoSG by comparing it with the classic 1OCA. Fig. 9(a) and 9(b) respectively refer to the output power and incremental cost of each generator. In Fig. 9(a), the variation pattern is similar to that in Fig. 5(a), but there are still differences, mainly reflected in the convergence speed and stable values. Different generators can converge to stable values in a short period of time at different time periods. There are certain differences between the output power and actual electricity consumption of each generator during low, peak, and off peak periods, and there are also significant differences in the output power of different generators during the same electricity consumption period. The optimal scheduling result for output power is (46.5, 29.4, 17.4, 69.5, 28.1, 37.6, 58.0, 24.6, 28.5) MW. In Fig. 9(b), the incremental cost of the generator gradually converges with the output power, and the incremental cost of power generation during the low, peak, and flat peak periods is consistent, with values of (7.456, 9.251, 5.621).

Table IV shows the total cost of two consistency algorithms in EDoSG. Compared to 1OCA, D2OCA has better optimal scheduling results. The generator costs of D2OCA in the first, second, and third time periods are 2.2475 million yuan, 5.8236 million yuan, and 3.7932 million yuan, respectively, which increases by 10.23%, 11.36%, and 13.36% compared to the corresponding time periods of 1OCA. Therefore, the proposed D2OCA application in the EDoSG problem model solving process can reduce the total cost of the generator. Therefore, D2OCA is effective and has higher convergence accuracy and speed compared to 1OCA.

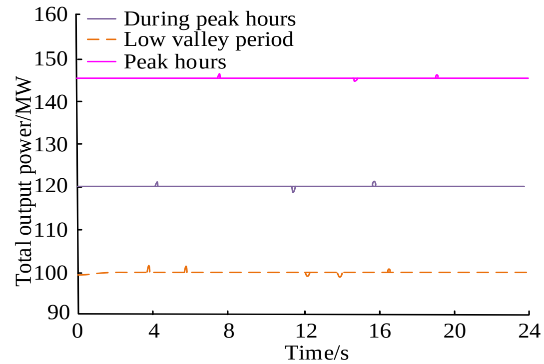
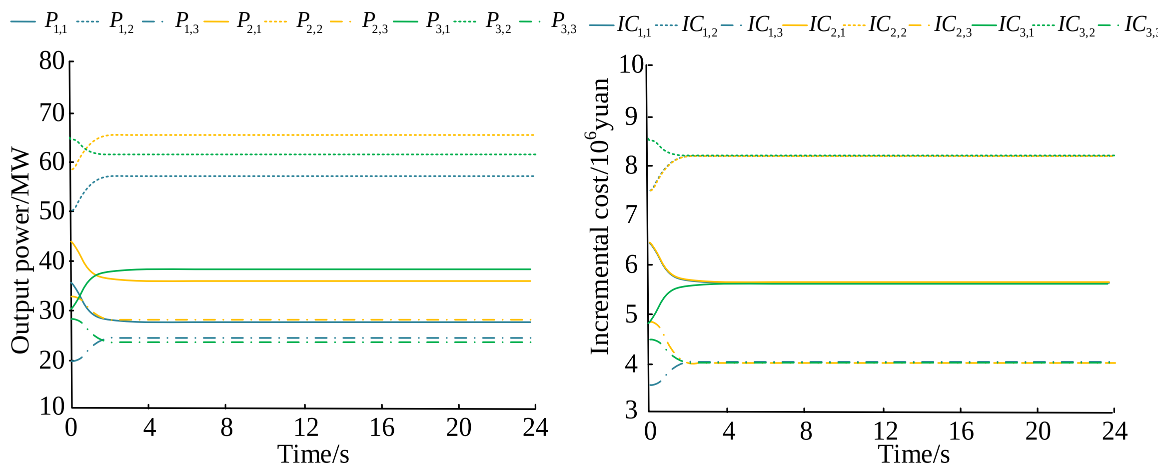


Fig. 8. Simulation results of actual total output in different time periods.



(a) Generated output power (b) Incremental cost

Fig. 9. Output power and incremental cost of each generator.

TABLE IV. THE TOTAL COST OF TWO CONSISTENCY ALGORITHMS IN SMART GRID ECONOMIC DISPATCH (106YUAN)

algorithm	varIable	Period 1	Period 2	Period 3	Total
1OCA	P_1	75.362	185.368	126.375	387.105
	P_2	76.465	176.341	119.351	372.157
	P_3	81.268	191.361	119.829	392.458
D2OCA	P_1	75.359	185.363	126.372	387.094
	P_2	76.463	176.337	119.349	372.149
	P_3	81.265	191.357	119.826	392.448

V. CONCLUSION

To achieve low-cost control of generators in EDoSG problems, this study innovatively proposed D2OCA based on the introduction of multi-agent consensus algorithms. The simulation of D2OCA showed that different generators could converge to a stable value in a short period of time at different time periods, and there were significant differences in the output power of different generators. The stable values of variable B_i for different generators during the same time period were the same, which were (-2.3816, -2.3715, -3.5029). The incremental cost of generators was consistent in the three time periods of low valley, high peak, and off peak, with a total cost of 6.0874, 9.4528, and 7.7068, respectively. Both a and b variables converged to a value of 0 in a relatively short period of time. The convergence speed during low valley periods was moderate, the convergence speed during peak periods was the slowest, and the convergence speed during off peak periods was the fastest. 1OCA could converge to a stable value in a short period of time for different generators at different time periods. There was a certain difference between the output power and actual electricity consumption of each generator during low, peak, and off peak periods. The application of D2OCA in the EDoSG problem model solving process could reduce the total cost of generators. The proposed EDoSG model still has limitations, such as the communication topology of the smart grid being connected and undirected, and the capacity constraints of the generator and ESU being able to find the optimal solution internally. The study did not take into account the charging and discharging limitations of the energy storage device. Instead, it was treated as a regular power source, which is not consistent with the actual system. Subsequent research on the economic scheduling problem of non-convex smart grids with energy storage device charging and discharging restrictions has certain practical significance.

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