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Distributed Optimal Dispatching of Multi-Entity Distribution Network With Demand Response and Edge Computing

JINGTING WANG AND YUEHUI PENG
North China Electric Power University, Baoding 071003, China
Corresponding author: Yuehui Peng (pyh06@ncepu.edu.cn)

ABSTRACT With large-scale penetrations of distributed generation (DG) and flexible loads, there will be multiple entities in traditional distribution network, such as distribution network operator (DNO), DG owner, and prosumers. Aiming at the collaborative optimization problem of distribution network among multiple entities, a distributed optimal scheduling approach of distribution network considering demand response and edge computing is proposed in this paper. Firstly, the virtual region decomposition method is proposed to divide the original distribution network into multiple regions according to different entities, and the bi-level optimization framework based on edge computing is constructed. Secondly, the optimal models of DNO, DG owner, and prosumers are established respectively, and the distributed optimal scheduling approach of distribution network with collaboration of control center and edge nodes is proposed. Then, the KKT conditions are adopted to realize the transformation of optimal models of DG owner and prosumers. Finally, the proposed distributed optimization scheduling approach is verified based on the modified IEEE33-node system. The results show that the proposed distributed optimal scheduling method can achieve better collaborative optimization among different entities in distribution network compared with the centralized optimization method.

INDEX TERMS Demand response, edge computing, distributed optimization, KKT transformation, optimal dispatching.

I. INTRODUCTION

In recent years, energy shortage and environmental pollution issues have caused widespread concerns. Distributed generation (DG) has developed rapidly due to its advantages of flexibility (such as micro-turbines) and environmental protection (such as wind power, photovoltaic, etc.). Besides, advanced two-way communication network and information technologies are being integrated to provide imperative facilities for enabling demand response (DR) programs, and the developments of customer-owned DGs and DR programs are transforming the traditional electricity users to the so-called prosumers [1], which causes the boundaries of power source and load in the traditional distribution network more and more blurred, and the traditional distribution network is moving towards an active distribution network with flexible operation mode and interaction among power source, network, and demand [2]. With the penetration of large-scale DG and flexible loads (FL, this paper assumes that prosumer works as a typical FL and only prosumer is considered in this paper for simplicity), the difficulty and complexity of distribution network operation have greatly increased. Considering that the DG and FL access distribution network has the characteristics of geographical dispersion, diversified entities, and the access points close to the edge of the distribution network, it is urgent to study optimal scheduling methods suitable for distribution network with multiple entities.

The optimal scheduling of distribution network is essentially a type of constrained optimization problem. That is, under certain constraints, the optimal function is obtained through optimizing the DG output, power consumption plan of prosumers, etc. A multi-stage optimization approach for active distribution network scheduling is proposed in [3], which takes into account the coordinated charging strategy of electric vehicles. A two-stage robust optimal dispatch model is built in [4], which is employed to address the uncertainties

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of photovoltaic generation in distribution network. A multi-time scale flexible resources coordination dynamic optimization scheme is presented in [5], which considers the smart loads' participation. The above research is mainly based on the centralized optimization mode, that is, the optimization decision is executed in the centralized control center of the distribution network, which collects the global information of the distribution network. However, in the distribution network containing DG and FL, there usually exist various entities in active distribution network, such as distribution network operator (DNO), DG owner, prosumers, and etc. Thus, it is a difficult task for traditional centralized optimization scheduling methods to solve this collaborative optimization problem with multiple entities. In response to the problems of the centralized optimization mentioned above, distributed optimization scheduling has become the research focus of scholars at home and abroad.

The general idea of the distributed optimization method is to decompose the original optimization problem into multiple sub-problems, and the original optimization problem can be solved through coordinated interaction among multiple sub-problems. And the distributed optimization methods can be divided into the following three categories: center-zone distributed optimization, center-unit distributed optimization, and completely distributed optimization. The basic idea of the first approach is to divide the distribution network into multiple areas based on the differences in optimization goals, and the optimization operation can be realized in a distributed manner through information interaction among adjacent areas. For example, a decentralized energy management framework is proposed in [6] to coordinate the power exchange between distribution system and networked microgrid based on the alternating direction method of multipliers algorithm (ADMM). Reference [7] establishes a distributed energy management framework for a multi-energy industrial park based on Stackelberg game theory, which considered the bi-directional energy demands conversion to realize the peak load shifting. A hybrid energy sharing framework of multiple microgrids is proposed in [8] with combined heat and power and DR, and a distributed optimization algorithm is used to solve the hybrid energy sharing problem. The second method is to build a bi-level coordination architecture and realize the collaborative optimization among different entities through electricity prices. For example, a bi-level framework is built for interactive dispatching between active distribution network and virtual micro-grid based on the analytical target cascading method [9]. Similarly, a bi-level scheduling framework is presented in [10] for optimal decision making of microgrid (MG) and battery swapping stations. The last method is to model the active distribution network as a distributed multi-agent system based on consensus theory, which realizes fully distributed optimization through information interaction among adjacent agents without central coordinator. For example, a consensus-based ADMM algorithm is discussed in [11] for solving the dynamic optimal power flow problem with DR, the distributed interior point method is employed to the optimal power flow problem of multi-area interconnected power systems [12].

With the development of the Internet of Things [13], [14], and high proportions of DG and FL penetration, the existing distributed optimization methods face the following two deficiencies: 1) There exist various decision makers who have conflicting optimal goals, which increases the difficulty of collaborative optimization with many entities. 2) There exists frequent information exchange with various entities, which puts forward higher requirements on the aforementioned distributed optimization methods, e.g., the network communication bandwidth, time delay of data transmission and processing, data privacy, etc. In this context, edge computing has received extensive attention from scholars at home and abroad. The basic idea is to offload part of the calculation tasks on centralized control center to the edge of the network, thereby reducing communication delay, reducing communication bandwidth requirements, alleviating the computing pressure of the control center and achieving data privacy protection of edge nodes [15], [16]. In power system, [17] builds a fog computing-based smart grid model and presents an efficient privacy-preserving scheme. Reference [18] presents a fog computing-based short-circuit diagnosis scheme with high diagnosis accuracy, robust fault tolerance, and shorter time delays. A three-tier edge-cloud collaborative residential energy management architecture is presented in [19], which improved the latency and processing performance. But for optimal scheduling of distribution network with multiple entities, there are no related studies taking into account edge computing.

To this end, a distributed optimal dispatching method of distribution network considering DR and edge computing is proposed in this paper. The contributions are as follows.

1) Considering the characteristics of DNO, DG owner, and prosumers in distribution network, a collaborative optimization framework is established between the control center and edge nodes based on the virtual region decomposition and edge computing.

2) A bi-level optimal model is constructed with price-based DR, and the distributed optimization is realized through information interaction among various entities.

3) A distributed solution algorithm is designed for solving the proposed optimal problem through cooperation between control center and edge nodes.

The rest of this paper is organized as follows. Section II introduces the distributed optimization framework based on edge computing. The optimal dispatching models of DNO, DG owner, and prosumers are presented in Section III. Distributed solution algorithms based on KKT transformation is illustrated in Section IV. And Section V analyzes numerical results, followed by concluding remarks in Section VI.

II. DISTRIBUTED OPTIMAL FRAMEWORK

A. VIRTUAL REGION DECOMPOSITION

Based on the idea of geographical partitioning of power system [22], this part proposes a region decomposition approach for decomposing the distribution network into virtual regions according to various entities, i.e., virtual region decomposition. Note that "virtual" means that, the proposed region decomposition is not to split the structure of distribution network physically, but to simplify the complex optimization problem with multiple geographically distributed entities. The basic principle of region decomposition is shown in Fig. 1, which takes the distribution network with DG (i.e., the distribution network includes two different entities: DNO and DG owner) as an example. And the original distribution network and be decomposed into two regions (i.e., distribution network region and DG region) through duplicating boundary bus N. More details about region decomposition could be found in [23], [24].

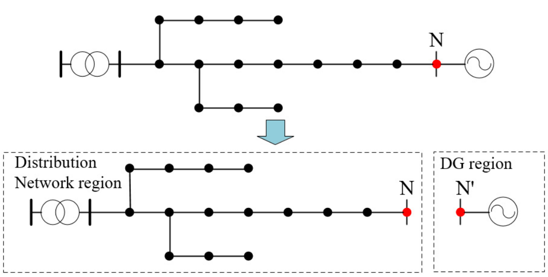

FIGURE 1. Virtual region decomposition of distribution network.

B. DISTRIBUTED OPTIMIZATION FRAMEWORK WITH EDGE COMPUTING

Based on the aforementioned virtual region decomposition method, a distributed energy management framework of distribution network with various entities is proposed in this part, which is a bi-level architecture with edge computing and DR. As shown in Fig. 2, the proposed optimization framework is an integration of cyber space and physical space. At the physical level, various entities of distribution network (i.e., DNO, DG owner, and prosumers) are connected together by power lines. At the cyber level, the control center of distribution network is used for calculation task of DNO's optimization model, whereas edge nodes are employed to execute the optimization tasks for DG owner and prosumers. And the collaboration between control center and edge nodes can be obtained through information interaction, i.e., DNO guides the behaviors of DG owner and prosumers by formulating the electricity price strategies, in return, DG owner and prosumers send their power generation or consumption plans back to control center in response to the price incentive.

III. DISTRIBUTED OPTIMAL DISPATCHING OF DISTRIBUTION NETWORK

As illustrated before, the optimal dispatching of distribution network can execute either in a centralized or distributed manner. The basic idea of centralized optimization is shown in the appendix, and the distributed optimization model of distribution network involves various entities, e.g., DNO, DG owner, and prosumers. The detailed optimization models are as follows.

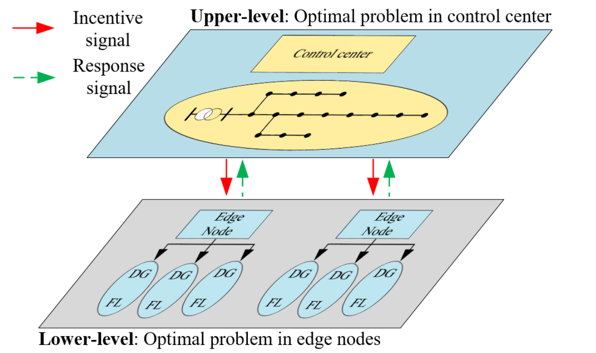

FIGURE 2. Bi-level optimization framework of distribution network with edge computing and DR.

A. OPTIMIZATION MODEL OF DNO

1) OBJECTIVE FUNCTION

The optimization goal of DNO is to minimize the operation cost of distribution network, which mainly includes the cost of purchasing electricity from the transmission network c_{DNO}, the cost of purchasing electricity from DG owner c_{DG}, and the cost of inducing prosumers for participation in DR c_{FL}, which are shown as follows:

$$c_{DNO} = c_{grid} + c_{DG} + c_{FL} \tag{1}$$

$$c_{grid} = \sum_{t=1}^{T} p_{grid,t} P_{grid,t} \tag{2}$$

$$c_{DG} = \sum_{t=1}^{T} p_{DG,t} P_{DG,t} \tag{3}$$

$$\begin{aligned} c_{FL} = & \sum_{t=1}^{T} c_{sub} |\Delta P_{DR,t}| \Delta t \\ & - \sum_{t=1}^{T} p_{sell,t} \max\{P_{FL,t} - \Delta P_{DR,t}, 0\} \\ & - \sum_{t=1}^{T} p_{DG,t} \min\{P_{FL,t} - \Delta P_{DR,t}, 0\} \end{aligned} \tag{4}$$

where, T is the number of time slots of the optimal scheduling. $p_{grid,t}$, $p_{DG,t}$, and $p_{sell,t}$ are the electricity purchase price from transmission network, the electricity purchase price from DG owner, and the electricity retail price to users in time slot t, respectively. c_{sub} is the unit subsidy cost for the power regulation of prosumers. $P_{grid,t}$, $P_{DG,t}$, $P_{FL,t}$, $\Delta P_{DR,t}$ denote the purchase power from transmission network, power from DG owner, power consumption of prosumers before implementing DR, and power regulation after implementing DR in time slot t, respectively. In which, $\Delta P_{DR,t} > 0$ means load reduction whereas $\Delta P_{DR,t} < 0$ represents enhancing power consumption.

2) CONSTRAINTS

The decision variables of DNO are the power purchase from transmission network, the electricity purchase price from DG owner, and the subsidy price for prosumers. In addition to the power balance constraints and line capacity constraints of distribution network, DNO guides the behaviors of DG owner and prosumers by formulating electricity price strategy, and the electricity price constraints should be also considered.

$$P_{grid,t} + P_{DG,t} = P_{CL,t} + P_{FL,t} - \Delta P_{DR,t} \tag{5}$$
$$P_{grid,\min} \le P_{grid,t} \le P_{grid,\max} \tag{6}$$
$$-P_{l,\max} \le P_{l,t} \le P_{l,\max} \tag{7}$$
$$p_{DG,\min} \le p_{DG,t} \le p_{DG,\max} \tag{8}$$
$$p_{sell,\min} \le p_{sell,t} \le p_{sell,\max} \tag{9}$$

where, Eq. (5) is power balance constraint, and the bound constraints of decision variables of DNO are given in (6)-(9). $P_{CL,t}$ is the conventional load (CL) of the distribution network in time slot t and $P_{FL,t}$ denotes the original flexible load(i.e., the output of prosumers) of the distribution network in time slot t before DR implementation, which assumes to be known through historical data. $P_{grid,max}$ and $P_{grid,min}$ are the upper and lower limits of power purchase from transmission network. $P_{l,t}$ denotes the active power flow of line l in time slot t. and $P_{l,max}$ is the maximum active power flow of line l. $p_{DG,max}$ and $p_{DG,min}$ are the upper and lower limits of the electricity purchase price from DG owner, $p_{sell,max}$ and $p_{sell,min}$ are the upper and lower limits of the electricity retail price to prosumers.

B. OPTIMIZATION MODEL OF DG

1) OBJECTIVE FUNCTION

The optimization goal of DG owner is to maximize its own profit, which contains the revenue from selling electricity to distribution network f_{cell} and local power generation costs c_{gen}.

$$f_{DG} = f_{sell} - c_{gen} \tag{10}$$
$$f_{sell} = \sum_{t=1}^{T} p_{DG,t} P_{DG,t} \tag{11}$$
$$c_{gen} = \sum_{t=1}^{T} a(P_{DG,t})^2 + bP_{DG,t} + c \tag{12}$$

where, as for c_{gen}, only the fuel cost is considered in this paper (Note that the renewable energy power generation ignores the fuel cost). a, b, and c are the cost coefficients of DG power generation.

2) CONSTRAINTS

The decision variable of DG owner is power output plan of DG, and the constraints mainly contain the power output and the ramping constraints of DG, which are shown as follows.

$$P_{DG,\min} \le P_{DG,t} \le P_{DG,\max} \tag{13}$$
$$-R_{DG}^{d} \le P_{DG,t} - P_{DG,t-1} \le R_{DG}^{u} \tag{14}$$

where, $P_{DG,max}$ and $P_{DG,min}$ are the upper and lower limits of DG's power output, R_{DG}^{u} and R_{DG}^{d} are the ramp-up and ramp-down rate of DG, respectively.

C. OPTIMIZATION MODEL OF PROSUMERS

1) OBJECTIVE FUNCTION

The optimization goal of prosumers is to minimize the electricity purchase cost with participation in DR program, which mainly includes the cost of electricity purchase from the distribution network c_{buy}, the penalty cost due to load regulation c_{pena}, and the benefit of DR subsidies f_{sub}.

$$c_{FL} = c_{buy} + c_{pena} - f_{sub} \tag{15}$$
$$c_{buy} = \sum_{t=1}^{T} p_{sell,t} \max\{P_{FL,t} - \Delta P_{DR,t}, 0\} + \sum_{t=1}^{T} p_{DG,t} \min\{P_{FL,t} - \Delta P_{DR,t}, 0\} \tag{16}$$
$$c_{pena} = \sum_{t=1}^{T} a_0(\Delta P_{DR,t})^2 + b_0(\Delta P_{DR,t}) + c_0 \tag{17}$$
$$f_{sub} = \sum_{t=1}^{T} c_{sub} |\Delta P_{DR,t}| \Delta t \tag{18}$$

where, a_0, b_0, and c_0 are cost coefficients of load regulation of prosumers.

2) CONSTRAINTS

The decision variable of prosumers is its DR strategy, this paper assumes that prosumers can be shifted within the dispatching period, but the total amount is guaranteed to be unchanged.

$$\Delta P_{DR,\min} \le \Delta P_{DR,t} \le \Delta P_{DR,\max} \tag{19}$$
$$\sum_{t=1}^{T} \Delta P_{DR,t} = 0 \tag{20}$$

where, $\Delta P_{DR,max}$ and $\Delta P_{DR,min}$ are the upper and lower limits of the power regulation of prosumers.

D. BI-LEVEL OPTIMIZATION MODEL OF DISTRIBUTION NETWORK

Based on the aforementioned optimization models of different entities in distribution network, a bi-level optimization model for distribution network with edge computing is constructed. At the upper level, DNO serves as the decision-maker who formulates the electricity price strategies to guide the behaviors of the DG owner and prosumers based on the centralized calculation of the distribution network. At the lower level, the intelligent terminals of distribution network are taken as edge nodes, through which the optimization schemes of DG owner and prosumers can be obtained with edge computing in response to the electricity price signals of DNO. The bi-level optimization model of distribution network is shown in Fig. 3.

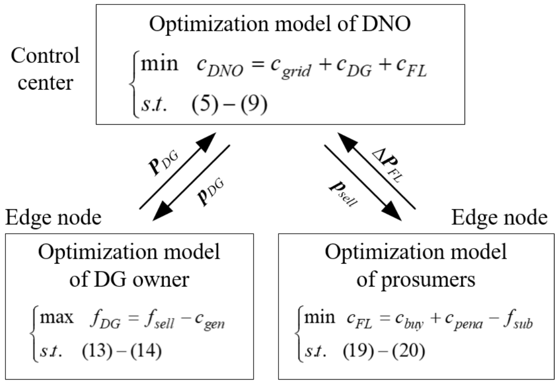

FIGURE 3. Bi-level optimization model of distribution network.

IV. SOLUTION ALGORITHM

Since the two-level optimization model mentioned in this paper involves multiple entities, KKT conditions are constructed on the lower-level DG and prosumers optimization sub-problems to simplify the complexity of solving the bi-level model.

For optimization problem of DG owner, i.e., (10)-(14), the KKT conditions are shown as follows:

$$\begin{aligned}
&p_{DG,t}+aP_{DG,t}+b+\lambda_{DG1,t}^{\max}-\lambda_{DG1,t}^{\min}\\
&\qquad\qquad+\lambda_{DG2,t}^{\max}-\lambda_{DG2,t}^{\min}=0\\
&0\leq(P_{DG,\max}-P_{DG,t})\perp\lambda_{DG1,t}^{\max}\geq 0\\
&0\leq(P_{DG,t}-P_{DG,\min})\perp\lambda_{DG1,t}^{\min}\geq 0\\
&0\leq(R_{DG}^{u}-P_{DG,t}+P_{DG,t-1})\perp\lambda_{DG2,t}^{\max}\geq 0\\
&0\leq(P_{DG,t}-P_{DG,t-1}+R_{DG}^{d})\perp\lambda_{DG2,t}^{\min}\geq 0\\
&(13)-(14)
\end{aligned}\tag{21}$$

where, $\lambda_{DG1,t}^{\max}$ and $\lambda_{DG2,t}^{\max}$ are the Lagrangian multipliers corresponding to the right-side inequalities of (13) and (14), whereas $\lambda_{DG1,t}^{\min}$ and $\lambda_{DG2,t}^{\min}$ are the Lagrangian multipliers corresponding to the left-side inequalities of (13) and (14), respectively.

Algorithm 1 Solution Process of DNO's Problem, Executed in Control Center of Distribution Network

1: Input data: Input the forecast power consumption of CL $\boldsymbol{P}_{CL}$.
2: Receive KKT conditions of DG owner and FL from edge nodes.
3: Solve the optimal scheduling problem.
minimize c_{DNO}
s.t. (6)-(10)
Obtain optimization results $\boldsymbol{P}_{grid}$, $\boldsymbol{p}_{DG}$, and $\boldsymbol{p}_{sell}$.
4: Send the price signals $\boldsymbol{p}_{DG}$, and $\boldsymbol{p}_{sell}$ to edge nodes.

For optimization problem of prosumers, i.e., (15)-(20), the KKT conditions are shown as follows:

$$\begin{aligned}
&-p_{sell,t}-p_{DR,t}+a_0\Delta P_{DR,t}+b_0\\
&\qquad\qquad+\lambda_{DR,t}^{\max}-\lambda_{DR,t}^{\min}+\mu_{DR}=0\\
&0\leq(\Delta P_{DR,\max}-\Delta P_{DR,t})\perp\lambda_{DR,t}^{\max}\geq 0\\
&0\leq(\Delta P_{DR,t}-\Delta P_{DR,\min})\perp\lambda_{DR,t}^{\min}\geq 0\\
&(19)-(20)
\end{aligned}\tag{22}$$

where, $\lambda_{DR,t}^{\max}$ and $\lambda_{DR,t}^{\min}$ are the Lagrangian multipliers corresponding to the right-side and left-side inequalities of (19), respectively. μ_{DR} is the Lagrangian multipliers corresponding to (20).

Thus, the solution process of the proposed optimal scheduling problem of distribution network with edge computing in this paper mainly includes two parts: 1) The solution of DNO optimization problem, which executed in the control center of distribution network; 2) The solution of DG owner and prosumers optimization problems(Formulate KKT conditions in this paper), which executed in edge nodes.

The solution process of DNO's optimization problem is shown in Algorithm 1, which mainly includes four steps: 1) Input CL forecast output of distribution network. 2) Receive the KKT conditions of DG and prosumers from edge nodes. 3) Solve the optimal scheduling problem denoted by (2)-(10). 4) Send the price signals to edge nodes.

The solution processes of the DG owner and prosumers' problems are shown in Algorithm 2 and 3, which mainly includes three parts: 1) Input the forecast output of renewable energy generation or the forecast load before implementing DR. 2) Receive the price signals from the control center of distribution network. 3) Solve the optimization models of DG owner or prosumers.

Algorithm 2 Solution Process of DG Owner's Problem, Executed in Edge Nodes

1: Input data: Input the forecast output of renewable energy generation.
2: Calculate the KKT conditions of optimization model of DG owner's problem, and send the obtained KKT conditions to control center.
3: Receive the price signal from control center $\boldsymbol{p}_{DG}$.
4: Solve the optimization problem denoted by (11)-(15), and obtain the optimal result $\boldsymbol{P}_{DG}$.

Algorithm 3 Solution Process of Prosumers' Problem, Executed in Edge Nodes

1: Input data: Input the forecast load before implementing DR $\boldsymbol{P}_{FL}$.
2: Calculate the KKT conditions of optimization model of prosumers' problem, and send the obtained KKT conditions to control center.
3: Receive the price signals from control center $\boldsymbol{p}_{sell}$..
4: Solve the optimization problem denoted by (16)-(21), and obtain the optimal result $\Delta\boldsymbol{P}_{DR}$.

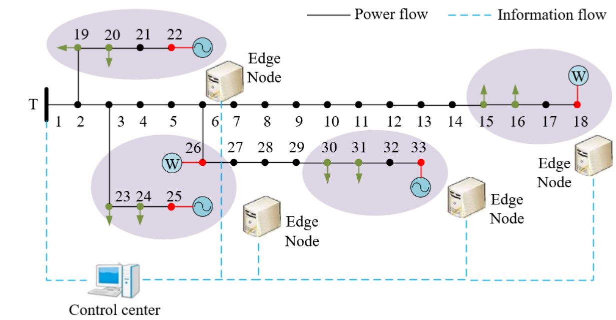

FIGURE 4. The topology of modified IEEE 33-bus distribution system.

TABLE 1. Parameters of DG.

DG Num	Node Num	P_{max} (MW)	P_{min} (MW)	Ramp (MW·h^{-1})	a	b	c
1	22	8	3	4	0.004	8.539	186.798
2	25	10	4	5	0.006	6.159	145.633
3	33	10	4	5	0.003	4.936	149.988
4	18	10	0	-	0	0	0
5	26	8	0	-	0	0	0

V. CASE STUDY

A. BASIC DATA

The modified IEEE33 node system is used for a case study, which is shown in Fig. 4. Among it, nodes 25 and 33 are equipped with 10MW gas turbines respectively, and node 22 is connected to 8MW gas turbines. Besides, nodes 18 and 26 are equipped with 10MW and 8MW wind turbines (WT) respectively. In addition, the load connected with nodes 15, 16, 19, 20, 23, 24, 30 and 31 are assumed FL (i.e.,prosumers) and the others are CL. The load data of distribution are derived from the actual operation data in Henan Province, China, and the total prediction load curve (i.e., the sum of CL and FL before implementing DR program) and the prediction output of WT in a typical day are shown in Fig. 5, the parameters of DG are shown in Table 1.

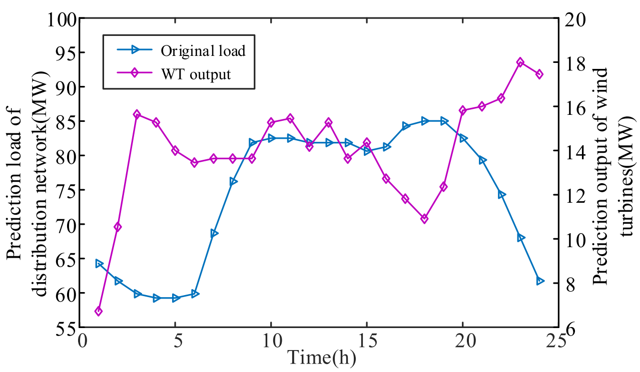

FIGURE 5. Basic input data of the case study.

B. RESULTS AND ANALYSIS

In order to verify the rationality of the distributed optimization method proposed in this paper, the following two cases are set for comparative analysis:

Case 1: The centralized optimization model (i.e., assuming that DNO, DG owner, and prosumers belong to an integrated entity) is used to conduct optimal scheduling of distribution network.

Case 2: The distributed optimization model proposed in this paper is used for optimal scheduling of distribution network.

1) OPTIMIZATION RESULTS OF CASE 1

Based on the generalized optimization model described part A in Section II, the goal of the centralized optimization of distribution network is to minimize its own operating costs, including the cost of purchasing electricity from transmission network, the cost of DG power generation, and the penalty of prosumers' power regulation. In this mode, the control center of distribution network can directly optimize the DG output and prosumers power regulation schemes (i.e., price signals are not considered), and obtain the scheduling results of DG output, power purchase plan from transmission network, and the power regulation strategy of prosumers, which are shown in Fig. 6 and Fig. 7.

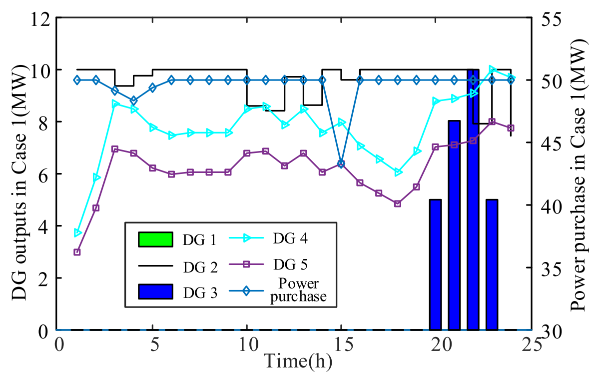

FIGURE 6. Optimal scheduling results of DG outputs and power purchase plan in Case 1.

2) OPTIMIZATION RESULTS OF CASE 2

The optimal results of electricity prices in distributed optimization mode are shown in Fig. 8, and the optimized DG outputs can be found in Fig. 9. Compared with Fig. 6, it is not difficult to find from Fig. 9 that in the centralized optimization mode, the goal of the distribution network is optimized through the power adjustment of DG (such as DG 25 and DG 33) since DG can be directly controlled by control center of distribution network. While in the distributed optimization mode, except that the output of the wind turbines (e.g., DG 18 and DG 26) is affected by the wind speed and fails to output at rated power, the remaining DG can maximize their own profits through rated power output.

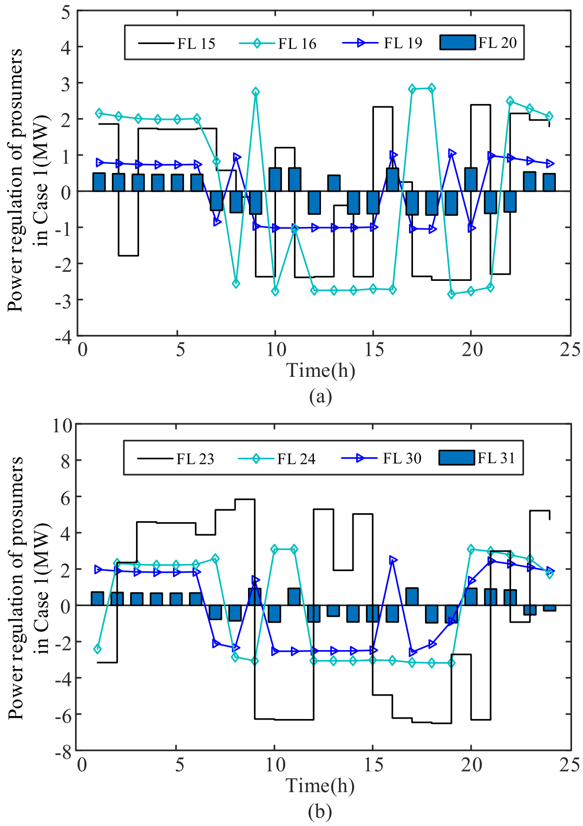

FIGURE 7. Optimal scheduling results of FL in Case 1.

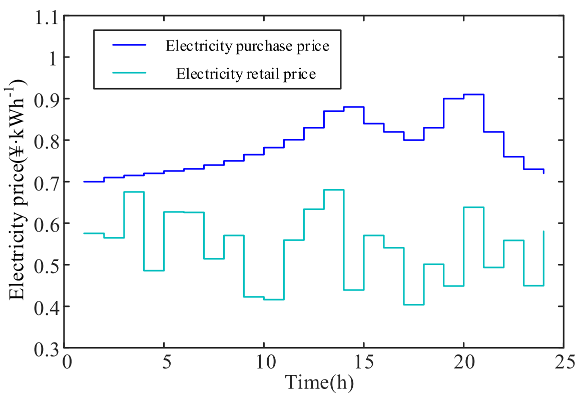

FIGURE 8. Optimal results of electricity prices in Case 2.

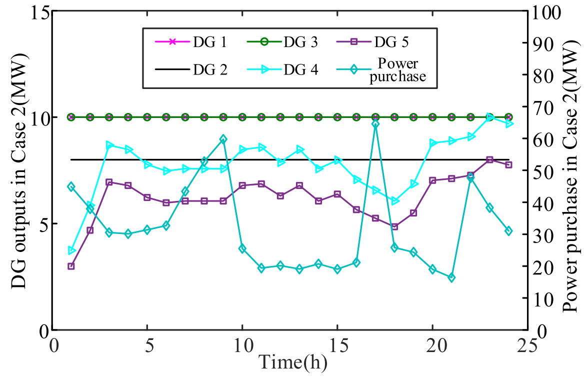

FIGURE 9. Optimal scheduling results of DG outputs and power purchase plan in Case 2.

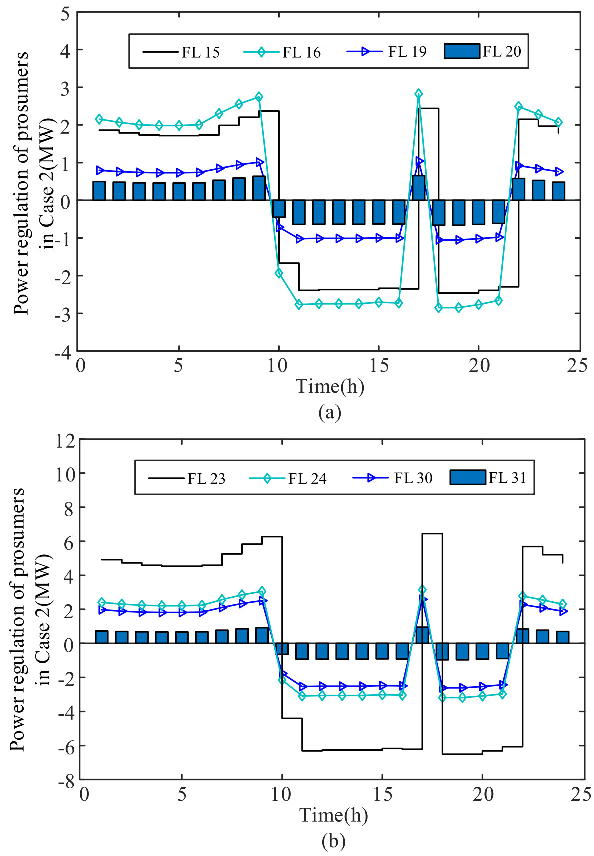

FIGURE 10. Optimal scheduling results of FL in Case 2.

The optimized prosumers' response strategies based on the electricity price are shown in Fig. 10. According to the load curve shown in Fig. 5, the load of the distribution network has a large peak-valley difference. And it is not hard to draw from Fig. 8 that the electricity retail price curve has a similar shape with the load curve of distributed network on the time scale, that is, the electricity price is also higher during the peak load period, which could better reflect the real-time relationship of electricity supply and demand and guide prosumers to change its own electricity consumption behavior. According to the DR results of prosumers shown in Fig. 10 (positive means load enhancement), the prosumers' DR behaviors of different nodes have high consistency, i.e., in the period of higher electricity prices, such as the time period 11:00-15:00 and 18:00-21:00, each prosumer carries out load reduction, whereas during the time period of the lower price, such as time period 1:00-6:00, the power consumption of prosumers increase, through which the total cost of prosumers is reduced. The comparison of the total load curve of the distribution network before and after implementing DR is shown in Fig. 11. It can be drawn from Fig. 11 that the dynamic electricity price mechanism adopted in this paper can reflect the real-time supply and demand of distribution network and has a significant effect on reducing the load peak-valley difference.

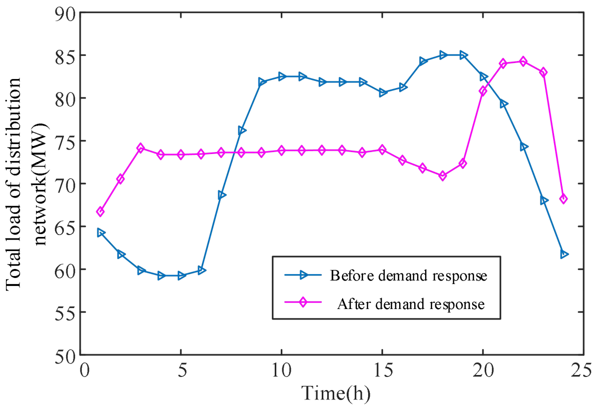

FIGURE 11. Comparison of load curves before and after DR in distributed optimization mode.

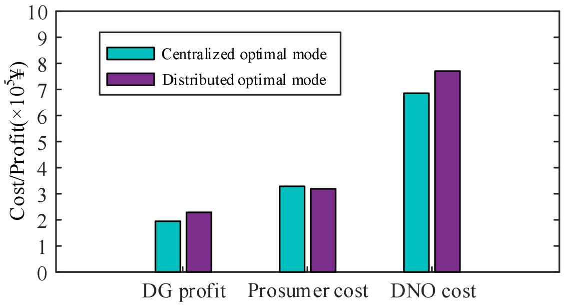

FIGURE 12. Economic comparison of centralized and distributed optimal modes.

For the DG outputs and prosumers' strategies obtained by the centralized optimization method, the objective function values of different entities are calculated according to (2), (11), and (16), respectively. The economic comparison of centralized and distributed optimization methods is shown in Fig. 12. According to Fig. 12, the revenue of DG in centralized mode is lower than that of in distributed mode, and the cost of prosumers in centralized mode is higher than that of in distributed mode. However, the operation cost of DNO in centralized mode is lower than that of in distributed mode. This is because the centralized scheduling model aims at minimizing the operation cost of the entire distribution network, and the total cost minimization is realized through reducing the DG's profit and increasing the prosumers' cost which fails to guarantee the benefits of DG owner and prosumers. In contrast, the proposed distributed optimal scheduling method can better achieve the coordination among the DNO, DG owner, and prosumers compared with centralized optimal scheduling, which verifies the rationality of the method proposed in this paper.

VI. CONCLUSION

In this paper, a distributed optimal dispatching method for distribution network with edge computing and DR is proposed, through numerical case study, the following conclusions are obtained:

1) The proposed energy optimization framework with DR and edge computing for distribution network is effective, which is suitable for distribution network optimization with various entities through virtual area decomposition.

2) Compared with the traditional centralized scheduling method, the distributed optimal scheduling method proposed in this paper can better achieve the collaborative optimization among DNO, DG owner, and prosumers in distribution network.

The impact of intermittent power generation sources (such as wind generation) and load volatility are not considered in this paper, and research on the optimal dispatching method of distribution network that takes into account uncertainties will be the further work.

APPENDIX

TRADITIONAL CENTRALIZED OPTIMIZATION

Under the traditional centralized optimization framework, the control center of distribution network is utilized for optimal dispatch decision-making, which based on SCADA, D5000 and other systems to collect operation information of distribution network for centralized optimal dispatching. The optimized scheduling model can generally be expressed in the following general form:

$$\begin{cases} \min & f(x, y) \\ s.t. & g(x, y) \leq 0 \\ & h(x, y) = 0 \end{cases} \tag{23}$$

where, f denotes the objective function of the optimal scheduling problem, g and h are inequality constraints and equality constraints of the optimization problem, respectively. x and y are decision variables.

In general, the objective function of the optimal scheduling problem of distribution network is the minimum operating cost of the distribution network, mainly considering the power generation cost of the DG, the carbon emission cost, the load interruption compensation cost, etc. Constraints generally contain power balance constraints, DG output constraints, line capacity constraints, etc. More details could be found in [20], [21].

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JINGTING WANG was born in Harbin, China, in 1999. She is currently pursuing the bachelor's degree, majoring in electrical engineering and automation, from North China Electric Power University. During her university days, she has published two articles (one employed in engineering technology and management; one employed in power technology research) and owned three patents. Her research interests include integrated energy systems and power system modeling. She won the second-class scholarship and the title of "Merit Student."

YUEHUI PENG received the master's degree in electrical engineering from North China Electric Power University, in 2009. From 2003 to 2011, he was working in the management of the research project. He is currently the Vice Director of the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources. He has published five papers in the last five years. His research areas include power quality management and integrated energy system management.