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Original Research

Supply-Side Load Optimization After Considering Environmental Cost

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Abstract

The wide application of renewable energy makes distributed power generation play an increasingly important role, which brings a certain influence to traditional power generation. In the overall environment of smart grid planning, reasonable optimization of load supply side will greatly reduce the cost of power generation, smooth the fluctuation of load, and improve the economy of energy utilization. The optimization of supply side load using time-of-use (TOU) could promote the optimal allocation of resources, which is conducive to the sustainable development of clean energy. This paper aimed at researching the operational mode of traditional power plant and wind power when considering the demand response TOU and considering the constraints of environmental cost, thermal power load, overall dispatching and other factors to optimize the operation mode. In this paper, a multi-objective optimization model with the objective function of minimum curtailment wind rate and maximum power generation profit was established. The effectiveness of the proposed model and the improved algorithm was verified by an example. This paper also provided some support for further research on supply-side renewable energy generation and thermal power optimization considering energy storage.

Keywords: demand response, environmental cost, multi-objective optimization, improved particle swarm optimization

Introduction

Introduction of the Supply Side

Supply Side Research

The literature [1] mentioned that the rapid growth of energy demand and limited resources have led to serious global concerns about the depletion of energy resources. Low profit margins and fierce competition have prompted industrial companies to seek ways to improve operational efficiency and reduce energy costs [2]. As a promising next-generation power system, a smart grid (SG) has been proposed, which involves constructing an intelligent power transmission system by implementing bidirectional power and information flow [3]. SG is a power grid including intelligent substation, smart distribution network, smart meter, smart appliances, renewable energy, an intelligent power generation system and energy storage system [4]. SG technology has enabled investment cuts in capacity expansion, enabling the intelligent dispatch of industrial power loads to be available, and accelerating the development of renewable resources to achieve cleaner power [5].

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Literature [6] points out that environmental issues and the prospect of an energy crisis motivated people to develop wind energy and further studied the intermittent nature of wind power. This feature of wind energy is also a major challenge for large-scale grid connections. Due to the development and utilization of wind energy, huge environmental benefits have led to increasing demand, which has higher requirements for its production reliability, operation and maintenance and the application of new technologies [7, 8]. [9] studied the interaction between wind energy and electricity market, while [10] analyzed the life cycle of wind turbines to consider their economics. However, wind power has its unstable and intermittent characteristics. Large-scale use will bring certain challenges to the safe and stable operation of the entire power system [11, 12].

Thermal power is currently the most common way of generating electricity in the world and the most mature technology. However, with the pressure brought about by economic progress, the sustainable development required for environmental protection has attracted more and more attention. Traditional power systems face different challenges. The start-stop schedule is a major component of the optimal operation of the power system, also known as unit commitment (UC). [13, 14] mentioned that the goal of UC is to minimize the cost of power generation.

Supply-Side Load Optimization

Many researchers have carried out many models and methods for UC problems in order to reduce the cost of traditional thermal power generating units and improve environmental efficiency [15, 16]. UC plays an important role in traditional regulated load scheduling optimization, but it needs to be further studied as to whether it can maintain certain advantages in the face of large-scale access to the grid of renewable energy in this region. Distributed energy management is particularly important in smart grids, especially in microgrid [17]. The optimal energy management for microgrid includes economic dispatch (ED), UC, and demand side management (DSM) [18]. The emergence of microgrid is to study the optimization problem between distributed energy and traditional power generation [19, 20]. The literature [21] study considers the UC problem of renewable energy impact, that is, the problem of load optimization on the power supply side. However, for cyclically undulating loads, frequent start-stop groups will increase costs. Therefore, the power side load optimization mentioned in the literature has certain limitations. This article was to plan the load of the whole unit's overall planning so that it could reduce the UC trouble caused by the cyclic floating load in a short period of time. Therefore, the variables of the start and stop of the thermal power generating unit were not considered as the objective function variables. The optimal dispatching in this paper could improve the safety and economy of regional microgrids to some extent.

Introduction of Demand Side

The increase in load demand puts a certain amount of pressure on the power supply side. In order to adapt to the growth of the load, the traditional construction cost of increasing the power equipment is huge, and the large demand for the load is also time-divided, which will inevitably result in a certain amount of waste of resources. With the development of SG-related technologies, DR is receiving more and more attention from various industries. [22, 23] point out that DR is an important form of DSM. The DR is more like a resource that can balance the power supply and demand in the power system to transfer the load [24]. The implementation of DR could reduce power demand during peak periods. Previous research on DR shows market and reliability aspects, applicability and user satisfaction, and their application optimization methods [25, 26]. Currently, DR is divided into incentive-based and price-based programs [27]. [28, 29] studied the economic impact of TOU. The above literature only flattened the demand curve through the price of electricity from the demand side of the grid. Although

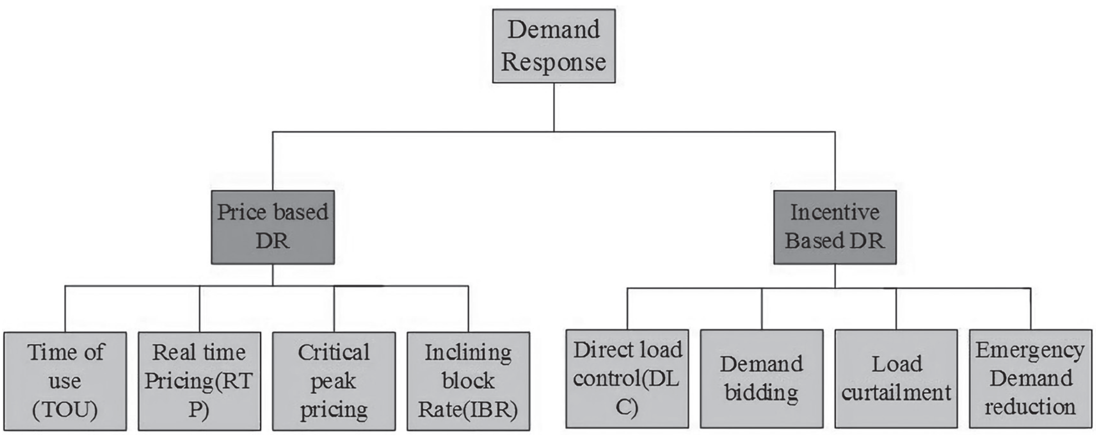

Fig. 1. Demand response classification.

it achieved a certain effect of cutting peak and valley filling, there was not enough research on the change of the supply side affected by renewable energy. Fig. 1 is a classification diagram of the demand response.

Joint Optimization Scheduling on the Supply and Demand Sides

After the implementation of the demand response TOU electricity price measure, the demand for power load will cause the peak-to-valley load value to fluctuate less, achieving a certain degree of reverse filling, that is, the relative power consumption during the daytime peak period is relatively reduced, and the evening trough period is that the amount of electricity used will increase. This is consistent with the power generation characteristics of wind power, which reduces the wind curtailment rate of wind power generation, improves the economics of production, improves the utilization rate of clean energy production, reduces environmental pressure, and is of great significance for sustainable development. Both supply- and demand-side optimization could play a role in reducing enterprise power generation costs, reducing resource waste and improving the deep utilization of resources. Then comprehensive consideration of the optimization of the supply and demand sides should have more significant effects. The main goal of joint optimal load scheduling is to minimize the total cost of the supply and demand side [30]. [31] proposed combining economic dispatching of renewable energy with demand-side management in microgrid. However, it did not highlight the optimization of renewable energy and traditional thermal power. [32] incorporated TOU and DR into dynamic economic scheduling problems, where TOU focuses on demand side and dynamic economic scheduling issues, with a focus on supply. On the demand side, it is desirable to reduce costs by adjusting the load of demand-responsive pricing [33]. The load change after the electricity price was studied. This part of the literature did not fully consider environmental factors and the economic benefits of environmental factors, and did not maximize the economy of renewable energy, so the economics obtained were not stable enough. In this paper, the above literatures would be integrated and the environmental cost of environmental factor transformation would be taken as one of the variables in the model.

Load Optimization Considering Environmental Costs

The pressure from energy shortages has always placed a high priority on how to maximize the economics of use. The environmental pollution caused by the traditional electric energy production process of fossil energy has prompted people to continuously strive to find renewable and clean energy that can supplement or replace conventional energy. Wind energy demonstrates its advantages and does not produce pollutants such as wastewater, waste gas, and particulate dust. [34] established a cogeneration microgrid system consisting of wind turbine (WT), photovoltaic array (PV), diesel engine (DE), micro turbine (MT), fuel cell (FC) and battery (BS). Considering the operating cost and pollutant treatment cost of the microgrid system, the comprehensive benefit maximization is selected as the objective function of dynamic economic dispatch. [35] established a model of the objective function including operating cost, pollutant treatment cost and load variance, and proposed an improved particle swarm optimization algorithm to solve. However, the literature only considers certain environmental factors to study the optimization of the supply side. Although intermittent and unstable wind energy is still a challenge to the power system, it should be paid more attention than the "environmental cost" saved by traditional thermal power [36]. In the literature, the complete environmental cost of thermal power and wind power was proposed and calculated from the aspects of pollutant SO_2, NO_X, CO_2, PM value, mining transportation and thermal pollution. There was a rigorous study on environmental cost in literature, however, there was also a lack of consideration on low-load operation of thermal power units on the supply side of the stable power grid.

According to the characteristics of thermal power plants, environmental costs could be divided into the cost of preventing the production of environmental pollution and the cost of environmental pollution caused by power generation. This paper analyzed the load optimization of traditional thermal power and renewable energy wind power, so it did not calculate the cost of environmental protection equipment that has been invested in the construction of thermal power, and only considered the cost of environmental pollution caused by power generation. The cost of environmental pollution loss from the perspective of preferential use of renewable energy was calculated from the optimization of wind energy and thermal power in this paper, where the fuel cost factor could be taken as a factor of comprehensive environmental cost to improve the accuracy of the research results.

In summary, the literatures were to optimize the load of microgrid involving distributed generation of renewable energy from certain aspects, and did not fully consider the environmental factors and the environmental economics. This paper was based on the load demand after the DR, and comprehensively considered the economics of environmental cost to optimize the dispatch of the supply side, including the distributed generation of renewable energy. In this paper, short-term periodic regular load demand would be studied. The research process would be to optimize the supply and demand under the background of regional micro grid, and the economic cost of environmental factor transformation would be taken as one of the variables. In this paper, the overall planning of thermal power units was substituted for the start-stop factor, and the calculation of fuel cost factor was highlighted so that the established model improves the safety and stability of low-load operation during valley load period. In this way, due to the real-time load situation, the fuel feeding cost and the corresponding calorific value of oil and fuel would be converted into the load to cushion the load fluctuation. This paper established a multi-objective model with the lowest wind yield and the largest profit, and used the improved particle swarm optimization algorithm to solve. As distributed generation, only wind power was considered in this paper.

Methods

Supply- and Demand-Side Considerations

Load After TOU

After the implementation of the demand response TOU, the demand for power load will cause the peak-to-valley load value to fluctuate less, achieving a certain degree of reverse filling, that is, the relative power consumption during the daytime peak period is relatively reduced, and the evening trough period is that the amount of electricity used will increase. The load change of the peak-to-valley value after the TOU price is not only related to the price of the two nodes, but also to the electricity price of other time periods.

$$\Delta Q_{d,s} = Q_{d,s}\left[E_s \cdot \frac{p_s^{'} - p_s}{p_s} + \sum_{\substack{s,t\in T\\ s\neq t}} E_t \cdot \frac{p_t^{'} - p_t}{p_t}\right] \tag{1}$$

…where $\Delta Q_{d,s}$ is the load response of the user in the actual s period after the TOU; $Q_{d,s}$ is the load demand for this period; E is the elastic coefficient matrix; E_s is the elastic coefficient matrix in the s period; p_s and p'_s are before and after TOU; p_t and p'_t are electricity prices before and after the change of t period; and T is the number of scheduling periods.

Environmental Costs

The environmental pressure brought by thermal power can be calculated by using a certain pollution index to calculate the cost, and the environmental cost saved can be regarded as a certain economic benefit:

$$\begin{cases} C_{c1} = \sum C_{c,s} = C_{SO_2} + C_{CO_2} + C_{NO_X} + C_{TSP} + C_{else} \\ C_{c2} = f^{'}(C_{oil})C_{oil} + \left[1 - f^{'}(C_{oil})\right]C_{oil} \\ C_e = C_{c1} \cdot \Delta Q + C_{c2} \end{cases} \tag{2}$$

…where C_{c1} represents the total environmental cost of coal combustion and C_{c2} is the cost of fuel, that is, when the thermal power unit load accounts for the total capacity ratio lower than the cost of oil injection during safe operation (the thermal power generation load at the time of oil injection also offsets the investment). The amount of oil corresponds to the difference between the loads, and the load corresponding to the amount of oil is converted according to the calorific value generated by the combustion of the oil), $f^{'}(C_{oil})$ is the fuel cost factor; C_{SO_2}, C_{NO_X}, C_{CO_2} , C_{TSP}, and C_{else} are the costs of SO_2, NO_X, CO_2, and *TSP* (total suspended particulate), and the cost of else factors. C_e is the environmental cost corresponding to the change in load, and ΔQ is the load change optimized on the supply side. Cost of environmental pollution loss, from the perspective of preferential use of renewable energy, that is, reduced the cost of renewable energy generation load ΔQ. Therefore, using the idea of the “penalty function” method to calculate the environmental cost into the objective function, the more the amount of thermal power generation, the more environmental costs will be reflected. In order to facilitate the calculation, this paper converted the environmental cost into the cost corresponding to the unit load, and the load of the optimized part changes linearly, so environmental cost and the optimized load were positively correlated.

Objective Function

Profit from Thermal Power Generation

$$r_c = p_c \sum_{i=1}^{I}\sum_{s=1}^{S} Q_{i,s}\left(1 - \theta_{c,i}\right) - C_f - \sum_{i=1}^{I} OD_{c,i} \tag{3}$$

In the formula, r_c is the profit of thermal power unit; p_c is the on-grid price of thermal power in the region; $Q_{i,s}$ is the generating power of unit i at time s; $\theta_{c,i}$ is the power consumption rate of unit i; C_f is the fuel cost of the thermal power unit; and $OD_{c,i}$ refers to other costs of thermal power units, including operation and maintenance costs.

UC can optimize the operation of the system. Many literatures considered starting and stopping primers to optimize operation and reduce costs. However, the frequent start and stop of thermal power generating units not only affects the cost and increases the manpower burden, but also damages the unit, especially the coal consumption of the unit. In the continuous few days, the load shows the peak of the day, and in the certain regular cycle of the valley value at night, the frequent start and stop shows a disadvantage. So the formula can be changed to:

$$r_c = p_c \sum_{s=1}^{S} Q_{a,s}^{c}\left(1 - \theta_c\right) - C_f - OD_{a,s}^{c} \tag{4}$$

In addition, different concepts of load expressions:

$$Q_{s,s}^{c}=Q_{n,s}^{c}(1-l)=Q_{a,s}^{c}(1-\theta_{c})(1-l) \tag{5}$$

$Q^{c}_{a,s}$ is the overall planned thermal power generation load, $Q^{c}_{n,s}$ means the on-grid load, and $Q^{c}_{s,s}$ is supply load.

This paper was to optimize the dispatching of wind power and thermal power in order to research the peak-to-valley load change after the TOU. It was assumed that the fluctuation trend of the load has been in a cyclical state for a short period of time, then all the thermal power generation. The units were seen as a whole to adjust the load to generate electricity. The total fuel cost under different loads is:

$$\begin{cases} C_{f}=p_{j}\sum_{i=1}^{I}f(Q_{i,s})+f^{'}(v_{i,s})\sum_{i=1}^{I}f_{0} \\ f_{i}(Q_{i,s})=m_{i}+n_{i}Q_{i,s}+l_{i}Q_{i,s}^{2} \end{cases} \tag{6}$$

…where C_f is the total fuel cost; p_j is the price of coal for power and electricity; f_o is the cost of fuel that helps stabilize the combustion of a thermal power unit under low operating load; and $v_{i,t}$ represents the ratio of unit i 's operating load to unit capacity at time. The purpose of oil injection is to make the boiler burn stably and prevent the unit from safe operation accidents caused by unstable combustion caused by poor coal quality. Thermal power generator sets, different unit capacity has different unit design coal consumption, but the actual operation of the fuel used is not completely standard coal, coal quality will also affect the actual value, which cannot be fully used as the design of coal consumption as a reference standard. m_i, n_i, l_i are the relevant parameters.

Wind Power Profit

$$r_{w}=p_{w}\sum_{s=1}^{S}Q_{a,s}^{w}(1-\theta_{w})-OD_{a,s}^{w} \tag{7}$$

…where r_w is the profit of wind power generation; p_w is the on-grid price of wind power in the region; $Q^{w}_{a,s}$ is the generating capacity of the unit at the moment; θ_w is the self-use power rate of wind power plant; and $OD^{w}_{a,s}$ is the operation and maintenance of wind power and other costs. Same as the power supply load of thermal power:

$$Q_{s,s}^{w}=Q_{n,s}^{w}(1-l)=Q_{a,s}^{w}(1-\theta_{w})(1-l) \tag{8}$$

…where $Q^{w}_{a,s}$ is the overall planned wind power generation load, $Q^{w}_{n,s}$ means the on-grid load, and $Q^{w}_{s,s}$ is supply load.

Wind Curtailment Rate

In this paper, one of the objective functions is curtailment rate, curtailment rate = curtailment air volume / (curtailment air volume + actual air volume). Since the amount of curtailment air and the actual amount of generated air are converted into the same method of generating power, the curtailment rate could also be calculated by replacing the power of both. The formula is:

$$\varepsilon=Q_{c,s}^{w}\Big/\left(Q_{c,s}^{w}+Q_{a,s}^{w}\right) \tag{9}$$

…where ε is the curtailment rate; $Q^{w}_{c,s}$ is the load corresponding to the curtailment air volume after the s period optimization; and $Q^{w}_{a,s}$ is wind power generation load.

Multi-Objective Particle Swarm Optimization Algorithm

Multi-Objective Model

The goal beyond multi-objective optimization (also known as multi-performance, multi-standard or vector optimization) is to minimize or maximize several objective functions simultaneously. The goal of multi-objective problems in the mathematical programming framework is to optimize various objective functions. Therefore, there is no longer a single optimal solution, but a set of non-dominated solutions [37]. The formula is:

$$\begin{aligned} &\min F(x)=(f_{1}(x),\mathrm{K},f_{n}(x))^{T} \\ &\mathrm{s.t}:\{x\in R|g_{i}(x)\leq 0,h_{j}(x)=0\} \end{aligned} \tag{10}$$

…where x is the solution vector of solution space E; F is the objective function vector; n is the number of solution functions; $p_i(x)$ is the general form inequality constraint; and $h_j(x)$ is the general form equality constraint. Under the condition that the time-sharing price and the curtailment rate of demand response are the smallest, the model that aims to maximize the profit of thermal power and wind power is:

$$\begin{aligned} &\min\varepsilon=\min\left(Q_{c,s}^{w}\Big/Q_{c,s}^{w}+Q_{a,s}^{w}\right) \\ &\max z=p_{c}\sum_{i=1}^{I}\sum_{s=1}^{S}Q_{a,s}^{c}(1-\theta_{c,i})-C_{f}-\sum_{i=1}^{I}OD_{c,i}+p_{w}\sum_{s=1}^{s}Q_{a,s}^{w}(1-\theta_{w})-OD_{w}-C_{e} \end{aligned} \tag{11}$$

Particle Swarm Optimization

The particles in the particle swarm optimization algorithm (PSO) move in the solution space, and each position in the moving process has a fitness value corresponding to it, and the smaller the fitness value is, the better [38]. The direction and distance of particle motion are determined by the velocity of the particle. The velocity is adjusted according to the movement of each particle, so that the optimal value is found in the solution space. The formula is:

$$V_i^{t+1} = w \cdot V_i^t + c_1 \cdot rand \cdot \left(q_{besti}^t - X_i^t\right) + c_2 \cdot rand \cdot \left(g_{besti}^t - X_i^t\right)$$
$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{12}$$

…where V_i^t is the velocity of the i th particle at the t th generation; X_i^t is the position of the i th particle at the t th generation; g^t_{besti} is the best experienced by the particle of the i th particle at the t th iteration position; g^t_{besti} is the best position experienced by all particles of the i th particle at the t th iteration; *rand* is a random number between 0 and 1; c_1 and c_2 are learning factors; and w is a weighting factor.

Because it is the joint optimization of the load of wind power and thermal power, a local extremum problem may occur in the process, which is similar to the basic optimization ability and convergence speed of the basic PSO. Therefore, the nonlinear change inertia weight can be used to improve PSO performance. The formula for adjusting w is:

$$w = w_{\max} - \left(w_{\max} - w_{\min}\right) * \arcsin \frac{t}{t_{\max}} * \frac{2}{\pi} \tag{13}$$

…where w_{max} and w_{min} are respectively the w maximum and minimum values; t is the current generation number; and t_{max} is the maximum number of iterations. When t is small, w is close to w_{max}, and the speed of w is also slower, which guarantees the global optimization ability of the algorithm; as t increases, w decreases nonlinearly, and the speed of w decreases rapidly, ensuring that the local optimization ability of the algorithm enables the algorithm to flexibly adjust the global optimization ability and local optimization ability.

Constraints

Load Balancing

$$\begin{cases} Q_{s,s}^c + Q_{s,s}^w = Q_d \\ Q^{\min} \le Q_{s,s}^c \le Q^{\max} \end{cases} \tag{14}$$

…where Q^{max} is the maximum load of unit capacity. Generally, for the safe and smooth operation of the thermal power generating unit, the long-term full-load operation is not selected to prevent the unit safety problem caused by the fluctuation of the load. The same Q^{min} indicates the lowest operating load for the safety of the unit. In this paper, $v_{i,s}$ is taken as the ratio of thermal power unit load to total capacity:

$$\begin{cases} v^{\min} \le v_{i,s} \le v^{\max} \\ v_{i,s}^{\min} Q_{a,s}^{\max} \le Q_{a,s}^c \le v_{i,s}^{\max} Q_c^{\max} \end{cases} \tag{15}$$

…where $v_{i,s} \ge 50\%$ (i = 1,2,2,4,5) indicates that the five units must maintain a load of more than 50% at the time of s. The function $f'(v_{i,s})$ indicates that when $v_{i,s} \ge 50\%$ is 0, the value of $v_{i,s} \le 50\%$ is 1.

$$f'\left(v_{i,t}\right) = \begin{cases} 0, v_{i,s} \ge 50\% \\ 1, v_{i,s} \le 50\% \end{cases} \tag{16}$$

According to the actual power generation operation of the thermal power plant, $70\% \le v_{i,s} \le 80\%$ is the optimal load ratio of the unit operation. At this time, the economic benefit is high, and the long-term full-load operation caused by the load fluctuation can also be prevented. Although the minimum load operation of the generator set is roughly 35%, in actual operation 50% is an important node for the safe operation of the unit. This paper was to research the cost profit of $v_{i,s}$ affected by 50% of this node, so we did not go deep into the $70\% \le v_{i,s} \le 80\%$ range.

Wind Power Output Constraints

$$\begin{cases} Q_{a,s}^w = W_Q \cdot W_P / \left(3600\eta 1 \cdot \eta 2 \cdot 1000\right) \\ Q_{a,s}^w \le \beta_s T_s \\ \varepsilon = Q_{c,s}^w / \left(Q_{c,s}^w + Q_{a,s}^w\right), \left(0 \le \varepsilon \le 1\right) \end{cases} \tag{17}$$

In the formula, β_s is the equivalent utilization rate in the s period; T_s is the installed capacity of the wind farm. W_Q (m^2/h) is air volume per hour; W_p(pa) is wind pressure; and $\eta 1$ and $\eta 2$ is the relevant parameter ($\eta 1$ is the fan efficiency of 0.719 to 0.8; $\eta 2$ is the mechanical transmission efficiency for the V-belt drive 0.95, for the coupling drive 0.98). Due to the influence of other technologies, policies and other factors, the paper is not a constraint. The purpose of this study is to use the minimum curtailment rate as the basic constraint. If the data ideal is likely to occur, the curtailment rate is 0 at a certain time.

Environmental Cost Constraint

$$0 \le \Delta Q \le Q_{a,s}^w$$
$$f'\left(C_{oil}\right) = \begin{cases} 0, v_{i,s} \ge 50\% \\ 1, v_{i,s} \le 50\% \end{cases} \tag{18}$$

The optimized load ceiling cannot exceed the maximum output of wind power, because the content of the study is the impact of wind energy output (also can be said that the wind rate) on the overall results. $f'(C_{oil})$ as a fuel cost function affects the overall environmental cost.

Materials

This study took the optimization of microgrid including thermal power and wind power in a certain area as an example. The parameter information

Table 1.Parameters table.

	MW	$f_{di}(Q_{i,t})$	OD_i	θ_i/%	l/%	p_s	p_c
Thermal	5*600	300	74	7.1	10	380	570
Wind	300		50	4.5	10	540	
Capacity	3300						

Table 2.Environmental cost parameters.

	SO2	NOX	CO2	CO	TSP	COAL ASH	SLAG
EPEG	0.33	2.88	643.89	0.094	0.144	39.57	10.79
PGC	0.95	0.95	20.0	16.7	4.0		
EVS	6.0	8.0	0.023	1.0	2.2	0.12	0.1

of the generator set is shown in Table 1. The second column in the table is the capacity of the unit, $f_{di}(Q_{i,t})$ is the standard coal consumption of thermal power, p_s is the price of electricity sold, and p_c is the coal price (yuan/ton). The costs associated with environmental impact factors in this area are shown in Table 2.

According to the load demand data of this area, the 24-hour load change was taken as the sample, and the utilization rate of the wind power plant was also compared and analyzed, as shown in Fig. 2. It could be seen from the figure that the demand trend of power load and the equivalent utilization rate of wind power generation are basically the reverse trend, which is beneficial to solving the problem of priority consumption of wind power. Two more prominent points could be taken as data for comparative study analysis. The equivalence ratio of wind power at the 11:00 of the sample is 26%, and the equivalent rate of the sample at 4:00 is 76%; the peak load at the two time points is exactly 3000 MW, and the valley load is 1400 MW.

For the basic calculation parameters of environmental costs, as shown in Table 2, environmental value standard/(yuan·kg^{-1}) refers to the environmental value corresponding to unit pollution; pollution gas capacity/(kg^{-1}), the pollution equivalent value indicates the relative relationship between pollution hazard and treatment cost between different pollutants or pollution emissions; emission of per electricity generated/(g/kw·h) indicates the pollution discharge corresponding to the unit power generation of thermal power enterprises.

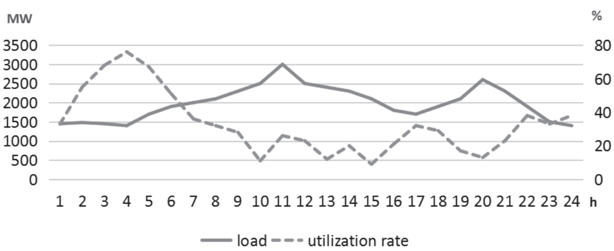

Fig. 2. Load and utilization.

Optimizing supply-side loads requires consideration of the priority use of renewable energy. Wind power output has anti-load characteristics. For this situation, the load scheduling of the demand response considering TOU can be divided into two scenarios: peak value and valley value. In this paper, the values of 4:00 and 11:00, both for load demand and the equivalent utilization rate of wind power, were in the extreme value, which could clearly show the optimization effect of the research results. After calculating the new load curve, the wind power was used first. If the objective function is satisfied, the optimization is stopped. If it is not satisfied, the constructed multi-objective model is solved by using the particle swarm algorithm. The model was calculated using Python. The two sets of solutions are load optimization of the peak and valley values after TOU.

Results and discussion

Results

Load After TOU

First, after implementing the TOU, the load change of day and night in a certain period of time would not

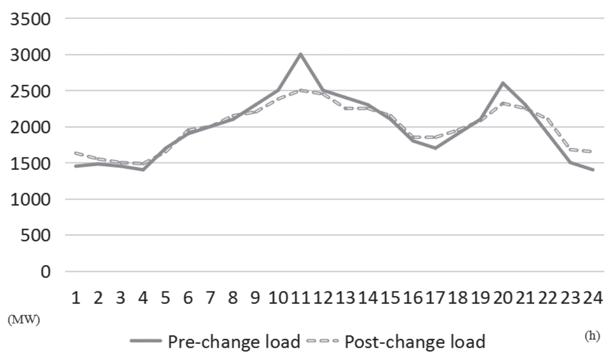

Fig. 3. Loads before and after TOU.

Table 3.Peak load distribution after TOU.

Q^1_d	$Q^c_{a,s}$	$Q^c_{n,s}$	$Q^c_{s,s}$	$Q^w_{a,s}$	$Q^w_{n,s}$	$Q^w_{s,s}$	$\Delta Q^c_{a,s}$	$f_i(Q_{i,t})$	C_T	C_e	r_c	r_w	z	α	ε	w_r	c_r
2500	2816.1163	2616.1720	2433.04	75	72	66.96	563.2233	840.3804	499016.8078		571107.3864	18880	569987.3864		0.0000	3%	97%
2500	2817.1497	2617.1320	2433.9328	74	71.04	66.0672	563.4299	840.6710	499182.4731	568.5183	571334.4013	18361.6	569127.4831	0.0004	0.0133	3%	97%
2500	2818.1830	2618.0920	2434.8256	73	70.08	65.1744	563.6366	840.9616	499348.14	1136.8713	571561.4148	17843.2	568267.7434	0.0007	0.0267	3%	97%
2500	2819.2164	2619.0520	2435.7184	72	69.12	64.2816	563.8433	841.2523	499513.8084	1705.2244	571788.4266	17324.8	567408.0022	0.0011	0.0400	3%	97%
2500	2820.2498	2620.0120	2436.6112	71	68.16	63.3888	564.0500	841.5429	499679.4785	2273.5775	572015.4369	16806.4	566548.2594	0.0015	0.0533	3%	97%
2500	2821.2831	2620.9720	2437.504	70	67.2	62.496	564.2566	841.8336	499845.1501	2841.9305	572242.4456	16288	565688.515	0.0018	0.0667	2%	98%
2500	2822.3165	2621.9320	2438.3968	69	66.24	61.6032	564.4633	842.1243	500010.8232	3410.2836	572469.4527	15769.6	564828.7691	0.0022	0.0800	2%	98%
2500	2823.3499	2622.8920	2439.2896	68	65.28	60.7104	564.6700	842.4149	500176.498	3978.6367	572696.4583	15251.2	563969.0216	0.0026	0.0933	2%	98%
2500	2824.3833	2623.8520	2440.1824	67	64.32	59.8176	564.8767	842.7056	500342.1743	4546.9897	572923.4623	14732.8	563109.2725	0.0029	0.1067	2%	98%
2500	2825.4166	2624.8120	2441.0752	66	63.36	58.9248	565.0833	842.9962	500507.8522	5115.3428	573150.4647	14214.4	562249.5219	0.0033	0.1200	2%	98%
2500	2826.4500	2625.7720	2441.968	65	62.4	58.032	565.2900	843.2869	500673.5316	5683.6959	573377.4655	13696	561389.7697	0.0037	0.1333	2%	98%
2500	2827.4834	2626.7320	2442.8608	64	61.44	57.1392	565.4967	843.5776	500839.2126	6252.0489	573604.4648	13177.6	560530.0159	0.0040	0.1467	2%	98%
2500	2828.5167	2627.6920	2443.7536	63	60.48	56.2464	565.7033	843.8682	501004.8952	6820.4020	573831.4626	12659.2	559670.2606	0.0044	0.1600	2%	98%
2500	2829.5501	2628.6520	2444.6464	62	59.52	55.3536	565.9100	844.1589	501170.5793	7388.7551	574058.4587	12140.8	558810.5037	0.0048	0.1733	2%	98%
2500	2830.5835	2629.6120	2445.5392	61	58.56	54.4608	566.1167	844.4496	501336.265	7957.1081	574285.4533	11622.4	557950.7452	0.0051	0.1867	2%	98%
2500	2831.6168	2630.5720	2446.432	60	57.6	53.568	566.3234	844.7403	501501.9523	8525.4612	574512.4463	11104	557090.9851	0.0055	0.2000	2%	98%

Table 4.Valley load distribution after TOU.

Q^2_d	$Q^c_{a,s}$	$Q^c_{n,s}$	$Q^c_{s,s}$	$Q^w_{a,s}$	$Q^w_{n,s}$	$Q^w_{s,s}$	Q_{fuel}	$\Delta Q^c_{a,s}$	$f_i(Q_{i,t})$	C_T	C_e	r_c	r_w	z	α	ε	w_r	c_r
1485	1486.3016	1380.7742	1284.12	225	216	200.88	34.882	262.3783	420.2250	362916.8114		201877.7995	96640	278517.7995	-1%	0.0000	14%	86%
1485	1487.3350	1381.7342	1285.0128	224	215.04	199.9872	34.882	262.5850	420.5117	363080.1943	568.3529	202107.0969	96121.6	277500.344	-1%	0.0044	13%	87%
1485	1488.3683	1382.6942	1285.9056	223	214.08	199.0944	34.882	262.7917	420.7983	363243.5789	1136.7060	202336.3927	95603.2	276482.8867	-1%	0.0089	13%	87%
1485	1489.4017	1383.6542	1286.7984	222	213.12	198.2016	34.882	262.9983	421.0849	363406.9649	1705.0590	202565.6869	95084.8	275465.4279	-1%	0.0133	13%	87%
1485	1490.4351	1384.6142	1287.6912	221	212.16	197.3088	34.882	263.2050	421.3716	363570.3526	2273.4121	202794.9796	94566.4	274447.9674	-1%	0.0178	13%	87%
1485	1491.4685	1385.5742	1288.584	220	211.2	196.416	34.882	263.4117	421.6582	363733.7418	2841.7652	203024.2706	94048	273430.5055	-1%	0.0222	13%	87%
1485	1492.5018	1386.5342	1289.4768	219	210.24	195.5232	34.882	263.6184	421.9449	363897.1326	3410.1182	203253.5602	93529.6	272413.0419	0%	0.0267	13%	87%
1485	1493.5352	1387.4942	1290.3696	218	209.28	194.6304	34.882	263.8250	422.2315	364060.5249	3978.4713	203482.8481	93011.2	271395.5768	0%	0.0311	13%	87%
1485	1494.5686	1388.4542	1291.2624	217	208.32	193.7376	34.882	264.0317	422.5182	364223.9188	4546.8244	203712.1345	92492.8	270378.1101	0%	0.0356	13%	87%
1485	1495.6019	1389.4142	1292.1552	216	207.36	192.8448	34.882	264.2384	422.8049	364387.3143	5115.1774	203941.4193	91974.4	269360.6419	0%	0.0400	13%	87%
1485	1496.6353	1390.3742	1293.048	215	206.4	191.952	34.882	264.4451	423.0915	364550.7114	5683.5305	204170.7026	91456	268343.172	0%	0.0444	13%	87%
1485	1497.6687	1391.3342	1293.9408	214	205.44	191.0592	34.882	264.6517	423.3782	364714.1100	6251.8836	204399.9842	90937.6	267325.7007	0%	0.0489	13%	87%
1485	1498.7020	1392.2942	1294.8336	213	204.48	190.1664	34.882	264.8584	423.6648	364877.5102	6820.2366	204629.2643	90419.2	266308.2277	0%	0.0533	13%	87%
1485	1499.7354	1393.2542	1295.7264	212	203.52	189.2736	34.882	265.0651	423.9515	365040.9120	7388.5897	204858.5429	89900.8	265290.7532	0%	0.0578	13%	87%
1485	1500.7688	1394.2142	1296.6192	211	202.56	188.3808		300.1538	472.6616	290726.5213	7956.9428	279565.6138	89382.4	338751.071	0%	0.0622	13%	87%
1485	1501.8021	1395.1742	1297.512	210	201.6	187.488		300.3604	472.9488	290890.2034	8525.2958	279794.6120	88864	337733.3162	0%	0.0667	13%	87%

appear to be large fluctuations. According to Formula (1), the load curve given above could be calculated to obtain the load after the influence of TOU. As shown in Fig. 3, the load curve showed a smooth trend. The load at the peak was significantly reduced, the load at the bottom was increased, and the load at the flat value fluctuates, but there was no large peak and valley. In addition, the role of TOU might also form the user's consumption habits to a certain extent, showing a stronger cycle stability. Therefore, under the influence of no other special factors such as bad weather, the load of the peak-to-valley value of the load for several consecutive days was stable after the implementation of TOU. For periodic load changes, it was more conducive to the economic dispatch of thermal power generation, and the unit was regarded as a whole to optimize and adjust, avoiding the increase of cost caused by frequent start-stop groups. The stability of the load also reduced the risk of climbing and sliding pressure caused by the large lifting load adjustment of the unit.

Peak Load Distribution After TOU

The peak load demand appeared at 11:00 of the daily working time. Although the TOU of demand response was reduced and transferred part of the load to some extent, the pressure on the power supply side was alleviated, but this time period is still the crucial period of electricity consumption. The load demand is still relatively high. In Table 3, α is the magnitude of the change in thermal power load, w_r is the ratio of the overall load of wind power, and c_r is the ratio of the overall load of thermal power. When Q_r^1 = 2500 MW, max$Q_w \geq Q_w$, minε = 0, max$z$ = 569987.3864. As can be seen from the optimization results, the equivalent utilization rate of wind power is at a low stage in the peak demand period. Due to the small proportion of wind power in the overall load, wind power generation can be connected to the Internet to the maximum extent, and thermal power generation can also be maintained at a better economic output range. For wind power generation, the decrease of power will lead to the increase of wind curtailment rate and the decrease of profit. Therefore, the optimal state in this period is the maximum wind power output, and the objective function is relatively ideal, so there is no need to optimize the load.

Valley Load Distribution After TOU

The optimization of the supply side after TOU was focused on analyzing the output of wind and thermal power generation in the valley period. As described in the above, during the valley period, the utilization rate of wind power generation was at a high period, and the load demand was at a low value even after TOU price was implemented.

The data provided in Table 4 is the valley load after TOU. At this time, when wind power and thermal power meet the minimum curtailment rate and maximum profit, the output ratio of the total demand load has different optimization results. Q_{fuel} represents load, which refers to the corresponding load value converted from the same calorific value generated in order to stabilize the combustion of thermal power units. When Q_d^2 = 1485 MW, $v_{i,s} \leq 50\%$, in order to stabilize the operation of the unit, oil is added to support combustion. Both C_f and Q_{fuel} need to be optimized constraints. minε = 0, max$Q^w_{a,s}$ = 225 MW, it achieves the maximum utilization effect of wind power in this period, however $Q^c_{a,s}$ = 1486.301608 MW, max$z$ = 278517.7995 yuan, $v_{i,s} \leq 50\%$, the economics and operational safety of thermal power are poor, and the profit is not the largest, so further optimization is needed. The result of $Q^w_{a,s}$ = 211 MW, $Q^c_{a,s}$ = 1500.768777 MW, $v_{i,s} \geq 50\%$, max$z$ = 338751.071 yuan, ε = 0.06 is in Pareto optimal state. It satisfied the objective function, and the economics and operational safety at this time were the best, and good optimization results were obtained to support the research in this paper.

Discussion

In order to distinguish the load optimization results of peak and valley values more clearly and discuss them appropriately, the results of the two time points were compared, as shown in Table 5.

In addition, the table also lists the results before and after the load optimization of the valley before the TOU affects the change. R_f indicates the result before optimization, and R_a indicates the result after

Table 5.Result analysis.

		Q_s		minε	max$z$	$v_{i,s}$
		$Q^c_{a,s}$	$Q^w_{a,s}$			
2500		2816.1163	75	0	569987.38	≥50%
1485	R_f	1486.3016	225	0	278517.79	≤50%
	R_a	1500.7687	211	0.06222	338751.07	≥50%
1470	R_f	1468.9398	225	0	274665.12	≤50%
	R_a	1500.9743	194	0.13778	336530.17	≥50%

optimization. It could be seen from Table 5 that at the peak, the maximum output of wind power will also get the highest profit; while in the valley, the curtailment rate ε = 6.22%, total profit z = 338751.071, it gets a better result. Comparing the load demand at 1470 MW, even if the thermal power unit maintains the maximum profit of 50% operation, the wind curtailment rate became relatively high, and there was no stability exhibited by the load at 1485 MW. In this way, the results ensured the safe operation of the thermal power unit, the smooth scheduling of the grid load, and at the same time achieved the goal of minimizing the wind curtailment rate and maximizing profits.

It could be seen from the research results that the scheduling optimization of demand load in the valley period is more complicated than peak period. The load transfer caused by the TOU also brought great convenience to the supply side. From the optimization results, it is not difficult to find that the model proposed in this paper and the environmental cost constraints including the fuel cost factor are also suitable and feasible.

Conclusions

The following conclusions could be drawn based on the results of our research:

1. After TOU, the entire load demand curve became smoother, and the function of cutting the peaks and filling the valleys was realized to some extent. The load transfer caused by TOU also brought great convenience to the supply side. Due to the load transfer, the thermal power plant could achieve a load output of 50% or so, in the case of a higher output of wind power. The results completed the objective function of minimizing the wind curtailment rate and maximizing profits, while at the same time ensuring the safe operation of the thermal power unit and the smooth scheduling of the grid load.
2. In this paper, TOU in demand response was adopted to peak cutting and valley filling for load demand of the power grid to some extent. Then, based on the new load curve, the model of minimum wind curtailment rate and maximum profit was adopted for optimization research. In this paper, the load capacity ratio was used as one of the limiting conditions for the safe operation of thermal power units in the low-load phase of the grid. At the same time, the fuel cost coefficient with similar properties was taken as one of the factors of the model and extended to the environmental cost to calculate the grid profit. According to the research results, our proposed scheduling scheme is feasible. The optimization results have better stability and greater environmental benefits, which shows that the factors in the environmental cost cannot be ignored.

   By using the multi-objective particle swarm optimization algorithm, this study maximized wind power generation while ensuring the minimum curtailment rate, and maximized the profit of high environmental benefits. This showed that the way of clean energy and the economic operation of thermal power generation was feasible, and it also showed the rationality of the research and the applicability of the actual results.
3. In this paper, wind power was only considered as a distributed energy source. With the penetration of multiple distributed energy sources, the optimization of the supply side would become more complicated. This paper also provided some ideas for future research on the relationship between the permeability of distributed energy and the optimization of the power supply side.

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Conflict of Interest

The authors declare no conflict of interest.

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