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Quantum particle swarm optimization for micro-grid system with consideration of consumer satisfaction and benefit of generation side

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Abstract: Considering comprehensive benefit of micro-grid system and consumers, we establish a mathematical model with the goal of the maximum consumer satisfaction and the maximum benefit of power generation side in the view of energy management. An improved multi-objective local mutation adaptive quantum particle swarm optimization (MO-LM-AQPSO) algorithm is adopted to obtain the Pareto frontier of consumer satisfaction and the benefit of power generation side. The optimal solution of the non-dominant solution is selected with introducing the power shortage and power loss to maximize the benefit of power generation side, and its reasonableness is verified by numerical simulation. Then, translational load and time-of-use electricity price incentive mechanism are considered and reasonable peak-valley price ratio is adopted to guide users to actively participate in demand response. The simulation results show that the reasonable incentive mechanism increases the benefit of power generation side and improves the consumer satisfaction. Also the mechanism maximizes the utilization of renewable energy and effectively reduces the operation cost of the battery.

Key words: micro-grid system; consumer satisfaction; benefit of power generation side; time-of-use electricity price; multi-objective local mutation adaptive quantum particle swarm optimization (MO-LM-AQPSO)

0 Introduction

At present, there have been much research on micro-grid optimization. As for the operation of micro-grid system, the linear cost function of renewable energy in the power generation side and the quadratic cost function of conventional energy in the power generation side were proposed, and day-ahead scheduling strategy is adopted to minimize the generation cost[1]. From the perspective of energy storage, an economic analysis was performed on the battery storage system of the micro-grid system under different configurations[2]. For the safety and stability of micro-grid system, the mesh adaptive direct search (MADS) algorithm was used to minimize the cost function of the system while constraining it to meet the consumer demand and safety of the system[3]. In order to ensure the economy and stability of the system, an energy management method based on the minimum service cost and energy storage state balance was proposed[4]. And an economic operation optimization method of micro-grid system based on scenario decomposition and scenario strategy aggregation mechanism was submitted[5]. In this literature, the operation cost and environmental cost of the micro-grid system were optimized and analyzed by improved genetic algorithm[6]. Based on the objective function of micro-power supply output and micro-grid operation cost minimization, the optimization model of micro-grid system was established to determine the output of each subsystem[7]. However, in Refs. [5-7], only the economy of micro-grid system is considered while the user side was not analyzed. An optimal dispatching method for micro-grid system considering translational load was proposed. The translational load model was established considering translational load units with different electrical characteristics, and the load translational solution strategy was proposed[8]. A hybrid genetic algorithm based on matrix real number and integers 0 and 1 was presented in Ref. [9]. By formulating reasonable charging and discharging strategies for electric vehicles, the electric bill of consumers can be reduced and the goal of peak-cutting and valley-filling can be achieved[10-11]. However, the researchers only

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consider the maximization of the economic benefits of the consumers while do not consider the impact of translational load on the consumer satisfaction in Refs. [8-11].

An improved particle swarm optimization (PSO) algorithm was adopted to study dynamic economic scheduling of micro-grid, but the problems such as premature convergence were not completely avoided[12]. Chaos grey Wolf algorithm was adopted to optimize the micro-grid from the perspective of economic scheduling, which improved the global search ability[13]. NSGA-Ⅱ optimization algorithm was adopted to optimize the micro-grid operation economy and load satisfaction[14]. However, it is easy to fall into the local optimal trap in Refs. [13-14]. In some litueatures multi-objective problems are transformed into single-objective problems to be solved[15-16], but the rationality and effectiveness of weight setting were difficult. The layered control strategy was adopted to meet the power demand and complete the optimized operation of the micro-grid system[17], but the stepped electricity price under the time-of-use electricity price was not considered. In this literature, the generation cost was analyzed from the system level of the micro-grid considering the time-of-use electricity price mechanism[18], but it did not conduct specific analysis and research on the operation cost in combination with the micro-source.

In our study, the multi-objective local variation-adaptive quantum swarm optimization algorithm is improved based on the comprehensive consideration of benefit of power generation and consumer satisfaction, and its Pareto optimal boundary is obtained. The translational load and time-of-use electricity price incentive mechanism are proposed, and the detailed research and analysis are carried out in combination with specific micro-sources.

1 Structure of micro-grid system

The structure of micro-grid system is shown in Fig. 1. It can be seen that the micro-grid system is composed of wind turbines, photovoltaic arrays, energy storage devices and energy management system. The types of load include interruptible load (translational load) and uninterruptible load (non-translational load). In our work, the dynamic optimization model of the power generation side and the consumer side is established, and the optimization of the micro-grid system is researched considering both the benefit of the power generation side and the consumer satisfaction.

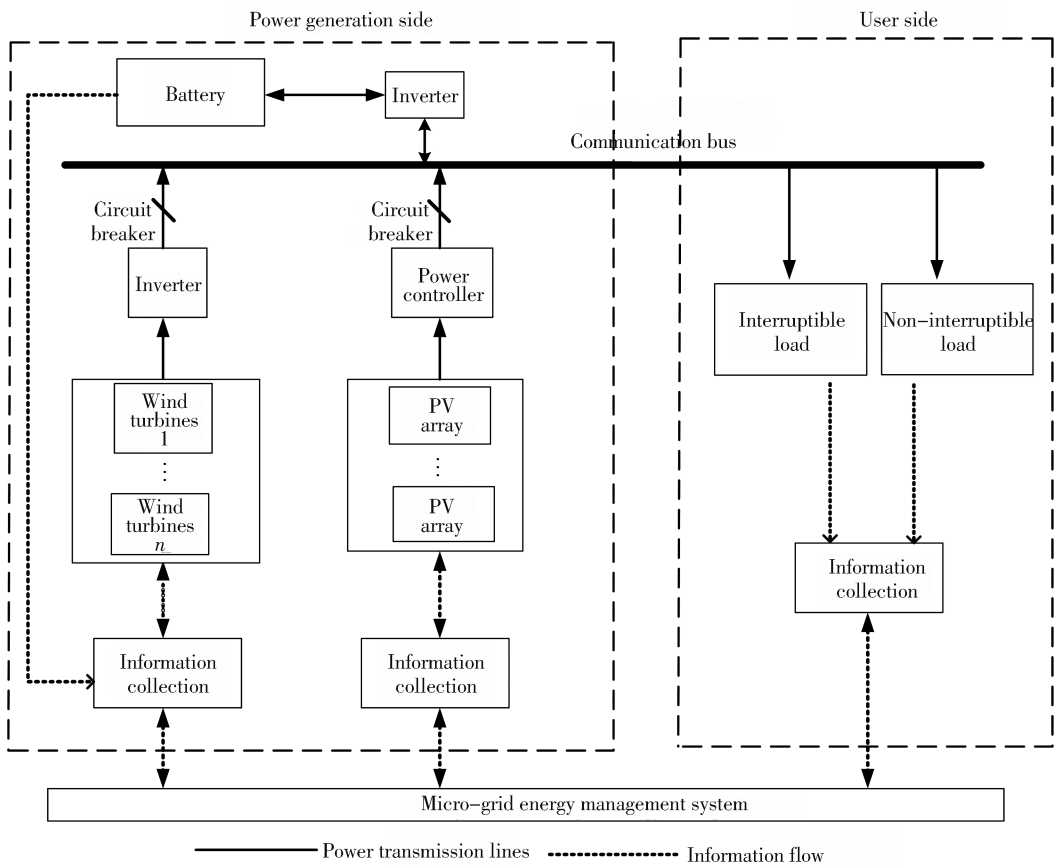

Fig. 1 Structure of micro-grid system

2 Dynamic optimization model

2.1 Model of benefit of power generation side

In our work, one of the objectives is to maximize the benefit of the power generation side with the isochronal step optimization with a span of 24 h, the specific expression is

$$F_1 = \sum_{t=1}^{24}\Big(\sum_{n=1}^{N} P_{n,\mathrm{PV}}(t) + \sum_{i=1}^{I} P_{i,\mathrm{WT}}(t)\Big)\times C_{\mathrm{price}} - C_{\mathrm{PV}} - C_{\mathrm{WT}} - C_{\mathrm{BAT}}, \tag{1}$$

where $P_{n,\mathrm{PV}}(t)$ and $P_{i,\mathrm{WT}}(t)$ are output power of photovoltaic arrays and wind turbines, respectively; N and I are the total number of photovoltaic arrays and wind turbine generator sets, respectively; C_{price} is Selling electricity tariff; and C_{PV}, C_{WT} and C_{BAT} are the operating loss costs of photovoltaic systems, wind turbines, and energy storage systems in micro-grid system, respectively.

1) Model of photovoltaic power generation system

The model of photovoltaic power generation system is expressed as

$$P_{\mathrm{PV}} = P_{\mathrm{STC}} G_{\mathrm{AC}} \frac{1+\omega(T_{\mathrm{C}} - T_{\mathrm{r}})}{G_{\mathrm{STC}}}, \tag{2}$$

where P_{PV}, P_{STC}, G_{AC}, G_{STC}, ω, T_{C} and T_{r} are the actual output power of the photovoltaic system, the maximum test power under standard test conditions, the actual illumination strength, the illumination strength under standard test conditions, the power temperature coefficient, and the actual working temperature of the photovoltaic system, respectively. T_{r} is reference temperature.

2) Model of wind power system

The model of wind power system is expressed as

$$P_{\mathrm{WT}} = \frac{1}{2}\pi\rho R^2 v^3 C_{\mathrm{p}}(v, \omega_r, \theta), \tag{3}$$

where ρ is the air density; R is the radius of the rotor; v is the wind speed; θ is the pitch angle; λ is the tip speed ratio, $\lambda = \frac{R\omega_{\mathrm{r}}}{v}$; and C_{p} is the wind energy utilization coefficient.

3) Model of energy storage system

The model of energy storage system is expressed as

$$E_{x,\mathrm{ESS}}(t+1) = (1-\omega)E_{x,\mathrm{ESS}}(t) + \eta_{x,\mathrm{c}}\delta_{x,\mathrm{ESSc}}(t)P_{x,\mathrm{ESSc}}(t)\Delta t - \frac{1}{\eta_{x,\mathrm{d}}}\delta_{x,\mathrm{ESSd}}(t)P_{x,\mathrm{ESSd}}(t)\Delta t, \tag{4}$$

$$\delta_{x,\mathrm{ESSc}}(t) + \delta_{x,\mathrm{ESSc}}(t) \leqslant 1, \tag{5}$$

where $E_{x,\mathrm{ESS}}(t)$ is the capacity level of energy storage system x in time period t; $P_{x,\mathrm{ESSc}}(t)$ and $P_{x,\mathrm{ESSd}}(t)$ are the charging and discharging power of the energy storage system in time period t, respectively; $\eta_{x,\mathrm{c}}$ and $\eta_{x,\mathrm{d}}$ are the charging and discharging efficiency of the energy storage system, respectively; ω is the self-discharge rate of energy storage; Δt is time interval; and $\delta_{x,\mathrm{ESSc}}(t)$ and $\delta_{x,\mathrm{ESSd}}(t)$ are the charging and discharging operation state (0/1) of energy storage system in time period t.

Equipment costs in the micro grid can be classified into fixed investment, equipment operation and maintenance costs, and energy storage system cost of wastage. The fixed investment expense shall be specifically analyzed in combination with the micro-grid system, but it does not affect the optimal operation of the micro-grid system. The calculation is not described here.

The operation and maintenance cost of wind power generation and photovoltaic power generation equipment are represented as

$$M_i = K_i P_i, \tag{6}$$

where M_i the operation and maintenance cost of equipment i; K_i is the operation and maintenance cost coefficient of equipment i; and P_i is the output power of equipment. The operation and maintenance cost of photovoltaic array is 0.009 6 (Yuan/kW). The operation and maintenance cost of the wind turbine is 0.009 6 (Yuan/kW).

In energy storage system, the operating wastage of battery is defined as

$$F_{\mathrm{B}}(\Delta(t) = \beta \mid P_{\mathrm{b}}(\Delta t) \mid \Delta t \times f(D_{\mathrm{b}}(t)), \tag{7}$$

$$f(D_{\mathrm{b}}, t)) = \begin{cases} 1, & 0 \leqslant D_{\mathrm{b}}(t) \leqslant D_{\max}, \\ \dfrac{f_{\mathrm{p}} - 1}{1 - D_{\max}}(D_{\mathrm{b}}(t) - D_{\max}) + 1, & D_{\max} < D_{\mathrm{b}}(t) \leqslant 1, \end{cases} \tag{8}$$

where $F_{\mathrm{B}}(\Delta t)$ is the operating wastage cost of energy storage system in time period Δt; β is the operating cost coefficient of the battery; $D_{\mathrm{b}}(t)$ and $P_{\mathrm{b}}(\Delta t)$ are the discharge depth and discharge power at time t; f_{p} is the penalty coefficient determined by discharge depth; and $D_{\max}$ is a threshold value.

2.2 Optimization model of consumer satisfaction

Optimization objective F_2 is the maximum consumer satisfaction. Through the sampling survey of consumers, it can be known that load satisfaction, user comfort and electricity price are important factors in user experience. Therefore, the definition of consumer satisfaction is considered from the following three aspects: load satisfaction, user comfort level, and electricity price. In order to better reflect consumers' electricity consumption experience and more comprehensively and objectively reflect consumers' satisfaction with electricity consumption, consumer satisfaction is defined in the form of multiplication of the three factors, and we obtain

$$F_2 = \frac{\sum_{t=1}^{24}\Big(\sum_{l=1}^{L}P_{\mathrm{w},l}(t)\Big)+\sum_{t=1}^{24}\Big(\sum_{l=1}^{L_2}P_{\mathrm{s},l}(t)\Big)}{\sum_{t=1}^{24}\Big(\sum_{l=1}^{L}P_{\mathrm{w},l}(t)\Big)+\sum_{t=1}^{24}\Big(\sum_{l=1}^{L_2}P_{\mathrm{I},L}(t)\Big)}\times \left(1-\frac{\sum_{t=1}^{24}\left(\frac{\Delta P(t)}{2}\right)}{\sum_{t=1}^{24}P_{\mathrm{load}}(t)}\right)\times\frac{\varepsilon_1\bar{P}_{\mathrm{price}}\sum_{t=1}^{24}P_{\mathrm{load}}(t)}{\sum_{t=1}^{24}\big(P_{\mathrm{price}}(t)P_{\mathrm{load}}(t)\big)}. \quad (9)$$

In Eq. (9), the first part is load satisfaction, the second part is customer comfort level, and the third part is price satisfaction. Among them, $P_{\mathrm{w},l}(t)$, $P_{\mathrm{s},l}(t)$ and $P_{\mathrm{I},L}(t)$ are the uninterruptible load power of unit equipment, the interruptible load power of unit equipment, and the maximum demand power of unit equipment in time period T, respectively; $\Delta P(t)$ is the transferred load; P_{load} is the total load demand; $P_{\mathrm{price}}(t)$ ($0.4\leqslant P_{\mathrm{price}}(t)\leqslant 1.2$) and $\bar{P}_{\mathrm{price}}$ are the selling price of micro-grid system and the consumer's expected price, respectively; and ε_1 is the influence factor.

2.3 Physical and operational limits

The power balance constraint is expressed as

$$\sum_{t=1}^{24}\Big(\sum_{n=1}^{N}P_{n,\mathrm{PV}}(t)+\sum_{t=1}^{I}P_{i,\mathrm{WT}}(t)+\sum_{t=1}^{24}P_{\mathrm{bat}}(t)=\sum_{t=1}^{24}\big(P_{\mathrm{load}}(t)-P_{\mathrm{unload}}(t)\big), \quad (10)$$

where N and I are the total number of wind turbines and photovoltaic array, respectively; $P_{n,\mathrm{PV}}(t)$, $P_{i,\mathrm{WT}}(t)$ and $P_{\mathrm{bat}}(t)$ are the output of unit photovoltaic array, wind turbine and battery at time t, respectively; $P_{\mathrm{load}}(t)$ is the load demand at time t; and $P_{\mathrm{unload}}(t)$ is the cutting load at time t.

The operation constraints of wind power system and photovoltaic system are expresses as

$$0\leqslant P_{n,\mathrm{PV}}(t)\leqslant P_{\mathrm{PV}}^{\max},\quad 0\leqslant P_{i,\mathrm{WT}}(t)\leqslant P_{\mathrm{WT}}^{\max}, \quad (11)$$

where $P_{\mathrm{PV}}^{\max}$ and $P_{\mathrm{WT}}^{\max}$ are the maximum output powers of unit photovoltaic array and wind turbine, respectively.

Energy storage system constraint is expressed as

$$\begin{gathered} E_{x,\mathrm{ESS}}^{\min}\leqslant E_{x,\mathrm{ESS}}(t)\leqslant E_{x,\mathrm{ESS}}^{\max},\\ \delta_{x,\mathrm{ESSc}}(t)P_{x,\mathrm{ESSc}}^{\min}\leqslant P_{x,\mathrm{ESSc}}\leqslant\delta_{x,\mathrm{ESSc}}(t)P_{x,\mathrm{ESSc}}^{\max},\\ \delta_{x,\mathrm{ESSd}}(t)P_{x,\mathrm{ESSd}}^{\min}\leqslant P_{x,\mathrm{ESSd}}\leqslant\delta_{x,\mathrm{ESSd}}(t)P_{x,\mathrm{ESSd}}^{\max},\\ 0.05E_{x,\mathrm{ESS}}^{\max}\leqslant E_{x,\mathrm{ESS}}(t)\leqslant 0.95E_{x,\mathrm{ESS}}^{\max},\\ E_{x,\mathrm{ESS}}^{\mathrm{st}}=E_{x,\mathrm{ESS}}^{\mathrm{fi}}, \end{gathered} \quad (12)$$

where $E_{x,\mathrm{ESS}}^{\min}$ and $E_{x,\mathrm{ESS}}^{\max}$ represent the minimum capacity and the maximum capacity of the energy storage system, respectively; $P_{x,\mathrm{ESSc}}^{\min}$ and $P_{x,\mathrm{ESSc}}^{\max}$ are the minimum charging power and the maximum charging power of energy storage, respectively; $E_{x,\mathrm{ESSd}}^{\min}$ and $E_{x,\mathrm{ESSd}}^{\max}$ are the minimum discharging power and the maximum discharging power of energy storage, respectively; and $E_{x,\mathrm{ESS}}^{\mathrm{st}}$ and $E_{x,\mathrm{ESS}}^{\mathrm{fi}}$ are the initial and final state of the energy storage system in the optimized period, respectively.

3 Proposed algorithm

3.1 Basic quantum particle swarm optimization

Quantum particle swarm optimization (QPSO) combines quantum theory with PSO. It makes use of the polymorphism and uncertainty of quantum behavior, so that particles can appear at any place in space with a certain probability. Instead of focusing on the moving speed of particles[19-20], QPSO determines the probability of particles appearing at a certain position at a certain time through the probability density function. By introducing the average best position, the global search ability of the algorithm is improved greatly. The QPSO is designed as

$$\begin{gathered} M_{\mathrm{b}}=\frac{1}{M}\sum_{i=1}^{M}P_i,\\ P=\gamma P_i+(1-\gamma)P_j,\\ X_i(t+1)=P\pm\beta\mid M_{\mathrm{b}}-X_i(t)\mid\times\ln\frac{1}{\mu},\\ \beta=1-\frac{1}{2}\frac{N_{\mathrm{iter}}}{N_{\mathrm{iterm}}}, \end{gathered} \quad (13)$$

where M is the population size; γ and μ are random numbers distributed on the interval of $[0,1]$; M_{b} is the average best position of particles; P_i and P_j are the individual optimal position and the global optimal position of the particle, respectively; $X_i(t)$ is the position where particle i iterates t times; β is accommodation coefficient; N_{iter} and N_{iterm} are the number of current iterations and the number of maximum iterations, respectively. Although the global search ability of QPSO algorithm has been improved, like the traditional PSO algorithm, it has great blindness in the initial stage and strong convergence in the later stage. It has not fundamentally solved the premature defect of the algorithm in the later stage. As the number of iterations increases, it is easy to fall into local optimization. Studies have shown that when B changes linearly, with the increase of iteration times, particle swarm will gradually gather and gather, and particle diversity will gradually decrease until stagnation[21].

3.2 LM-AQPSO algorithm

In order to overcome the shortcomings of QPSO algorithm, we propose an improved local mutation adaptive QPSO algorithm based on Ref. [22], called LM-AQPSO algorithm.

3.2.1 Local variation strategy

At the end of each crossover mutation, the optimal solution of the particle is cross-mutated in a small scale and compared with the original optimal solution to prevent the algorithm falling into the local optimal solution.

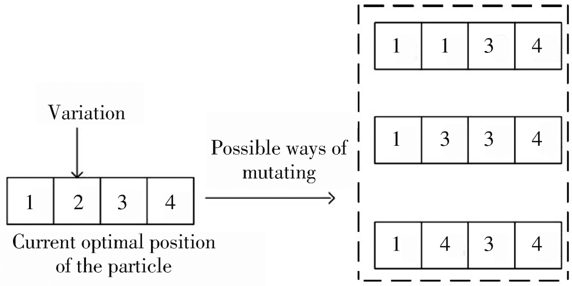

Fig. 2 Case of local mutation

3.2.2 Parameter dynamic adjustment strategy

According to Eq. (13), only β in the QPSO algorithm is tunable, which not only makes the QPSO algorithm easy to implement, but also makes the selection more important. Generally speaking, β decreases linearly with the increase of the number of iterations, and it is easy to fall into local optimization. Therefore, we introduce two indices, particle evolution degree and particle aggregation degree, and then obtain

$$L_1(k) = \frac{1}{2}\sqrt{[P_{\text{m}}(k) - P_{\text{gb}}(k)]^2 + [P_{\text{m}}(k) - P_{\text{bad}}(k)]^2},$$
$$L_2(k) = \sum_{k=T-t}^{T}[P_{\text{gb}}(k)/P_{\text{gb}}(K-1)], \tag{14}$$

where $L_1(k)$ and $L_2(k)$ are the particle evolution degree and the particle aggregation degree, respectively; $P_{\text{bad}}(k)$ is the worst case of particle swarm; T and t are observation time and observation period, respectively; When L_1 and L_2 are less than a certain threshold, particle swarm can be regarded as slow evolution with low diversity, and particle swarm may be trapped in local optimum. At this point, by adjusting β, the problem of the local optimal trap can be improved as

$$\beta = \frac{\beta + c}{1 + c}, \tag{15}$$

where c is a constant, and c is set to be 0.07.

3.3 Multi-objective optimization algorithm based on LM-AQPSO

Multi-objective optimization aims to obtain a set of non-dominated optimal solutions. At this time, the existence of global optimal solutions is no longer reasonable. Therefore, in order to adapt to multi-objective optimization problems, LM-AQPSO algorithm is adjusted, in which the object of local variation is adjusted to Pareto optimal solution. Thus, the individual optimal position and the average optimal position in Eq. (13) are expressed by Pareto optimal solution, and the concept of global optimal is not considered. The particle position updating equation is adjusted to

$$P = \gamma P^{\zeta}_{\text{Pareto}}(t),$$
$$X_i(t+1) = P \pm (1-\gamma)\beta \mid P^{\zeta}_{\text{Pareto}}(t) - X_i(t) \mid \ln(1/\mu), \tag{16}$$

where $P^{\zeta}_{\text{Pareto}}(t)$ is the ζth solution of Pareto optimal solution; ζ is the random integer within $[0, m_2]$, and m_2 is the number of solutions in Pareto optimal solution set.

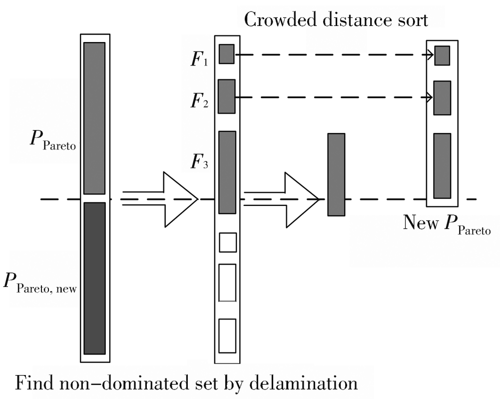

Fig. 3 Hierarchical sorting algorithm

The multi-objective LM-AQPSO algorithm called MO-LM-AQPSO is shown in Fig. 3. And the specific steps of MO-LM-AQPSO algorithm are as follows:

1) Particle swarm P_p is initialized and the number of particles m_1 is set in particle swarm P_p; optimal solution P_{Pareto} is initialized and the number of solutions m_2 is set in the optimal solution P_{Pareto}; maximum iteration number is set.

2) Find the non-dominated set $P_{Pareto,new}$ from the particle swarm.

3) As shown in Fig. 3, the original optimal solution set P_{Pareto} is merged with the non-dominant solution set $P_{Pareto,new}$, and the new P_{Pareto} is obtained by hierarchical sorting method. The specific process is as follows: firstly, all non-dominant solutions in $P_{Pareto} \cup P_{Pareto,new}$ are solved and put into the set F_1. Next, the solutions of F_2 are removed from $P_{Pareto} \cup P_{Pareto,new}$, and we continue to find the non-dominant solution in the remaining solution, and put it into the set F_2 until we have done with all the elements of $P_{Pareto} \cup P_{Pareto,new}$.

4) The crowding distance is used to sort all the elements in $F=F_1 \cup F_2 \cup F_3 \cup \cdots$ from large to small. The crowding distance equals the distance that is the sum of two fronts and a rear solution on all objective functions, and the crowding distance of edge nodes is set to infinity. As shown in Fig. 3, after sorting, the first m_2 solutions are selected as the new optimal solution set P_{Pareto}.

5) The P_{Pareto} optimal solution set is observed and local variations are made. According to Eq. (16), P_p is updated with the new Pareto optimal solution set to obtain the new particle swarm $P_{p,new}$. Then, as in steps 3 and 4, merging P_p and $P_{p,new}$. The new P_p particle swarm is obtained by hierarchical sorting method.

6) Determine whether the maximum number of iterations is reached. If the maximum number of iterations is reached, the search will end and the optimal solution set P_{Pareto} will be output. Otherwise, go to step 2 and continue with the iterative search.

3.4 Optimization process

The MO-LM-AQPSO algorithm is adopted to obtain the Pareto optimal boundary with the goal of the maximum benefit on the power generation side and the maximum user satisfaction. The day-ahead optimization set the number of particle swarm to be 200, the size of the optimal solution set to be 50, and the maximum number of iterations to be 200. The flow chart of day-ahead optimization is shown in Fig. 4.

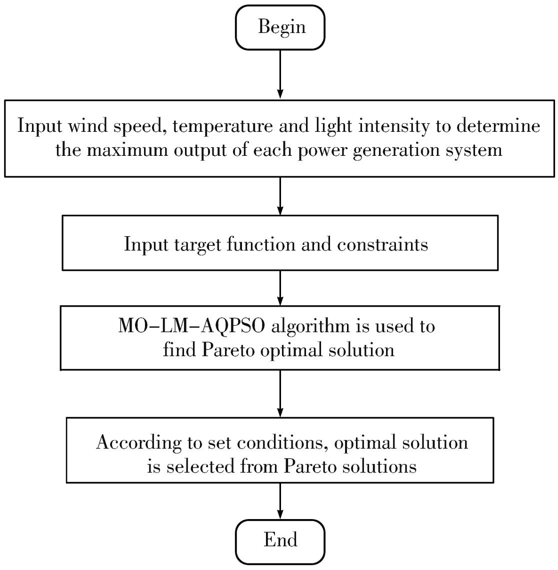

Fig. 4 Flow chart of day-ahead optimization

4 Results and discussion

4.1 Parameter settings

The parameters of wind power generation equipment, photovoltaic power generation system and energy storage system are shown in Tables 1—3.

Table 1 Parameters of wind turbine

Wind turbine	1	2	3	4	5
Rated power (kW)	15	15	15	15	10

Table 2 Parameters of photovoltaic array

Photovoltaic array	1	2	3
Rated power (kW)	30	25	20

Table 3 Parameters of energy storage system

Equipment	Specification (V/(A·h))	Quantity	Capacity (kW·h)
Lead acid battery	2/1 000	980	200

The predicted wind speed, temperature, light intensity and load demand in a day are shown in Fig. 5. The total load demand of the whole day is 1 273.8 kW, among which the demand of uninterruptible load is 733.2 kW. The starting power of the battery is required to be 1/2 of the maximum capacity, and the starting and ending states of the battery are the same.

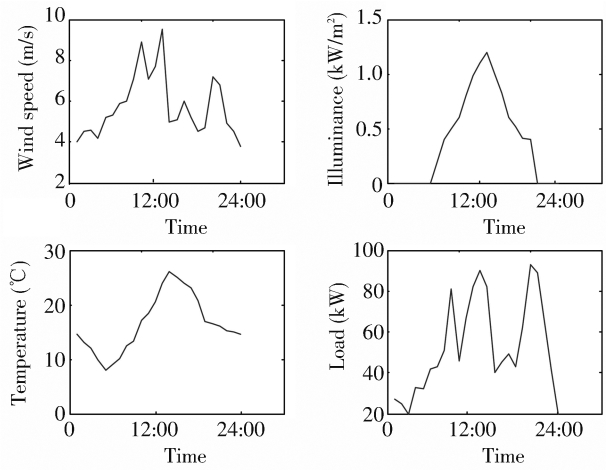

Fig. 5 Prediction curves of wind speed, light intensity, temperature and load

4.2 Analysis of results

Strategy1: Without considering translational load and time-of-use electricity price.

By optimizing the objective function, the Pareto solution considering benefit of power generation and consumer satisfaction can be obtained, as shown in Fig. 6.

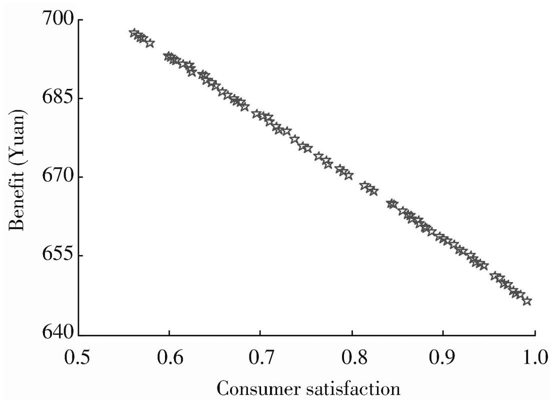

Fig. 6 Pareto solution considering of power generation benefit and consumer satisfaction

A calculation strategy of power shortage loss considering satisfaction-related constant is introduced, which can be obtained by combining Ref. [23] and expressed as

$$C_{\mathrm{loss}}(W_{\mathrm{loss}},\tau)=\frac{\alpha_1\alpha_2W_{\mathrm{loss}}^2}{W_{\mathrm{R}}}+\beta_1(W_{\mathrm{loss}}-W_{\mathrm{loss}}\tau), \quad (17)$$

where C_{loss} is the loss caused by insufficient electric quantity, α_1 and β_1 are the variable constants related to the missing electric quantity, α_2 is the variable constants negatively related to satisfaction, W_{R} is the maximum demand electric quantity, W_{loss} is the lack of electric quantity, and τ is the user type, $\tau\in[0,1]$.

An optimal solution is selected to maximize the benefit of power generation. It can be seen from Fig. 7 that when the consumer satisfaction is 91.5%, the maximum benefit of the power generation is 653.2 Yuan. Meanwhile, according to the simulation results, the selling price is 0.63 Yuan/(kW·h), and the daily supply is 1 167 kW·h. The output of each system after optimization is shown in Figs. 8 and 9. The state of the battery, the load demand power and actual generation side supply are shown in Figs. 10 and 11.

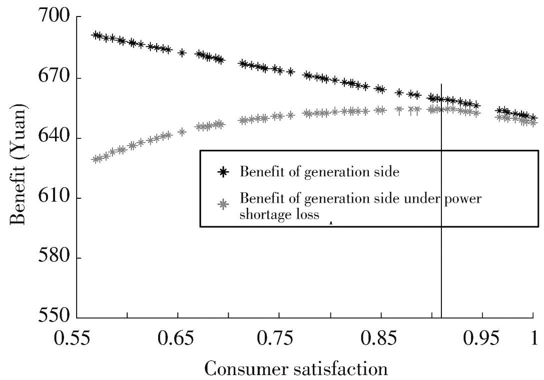

Fig. 7 Benefit of power generation diagram

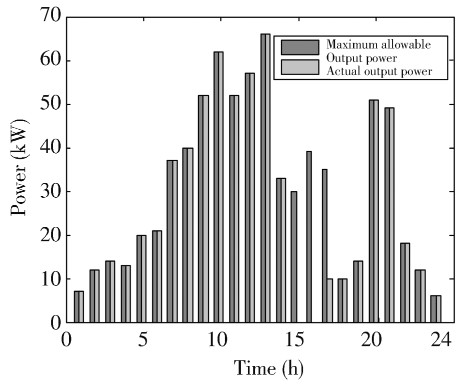

Fig. 8 Maximum allowable output power and optimized output power of wind power generation system

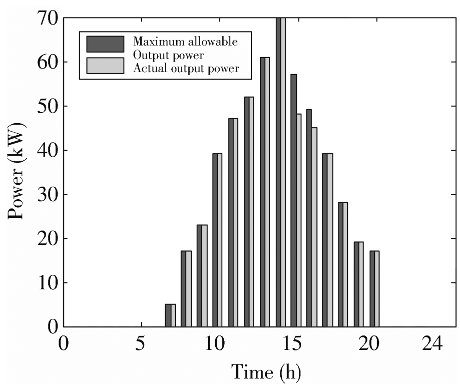

Fig. 9 Maximum allowable output power and optimized output power of photovoltaic system

As shown in Fig. 8, the output power of wind power generation does not reach the maximum point in 15:00—17:00. As shown in Fig. 9, the output power of photovoltaic power generation does not reach the maximum point in 15:00—16:00. The renewable energy is not fully utilized. As the cost of wind power generation is greater than that of photovoltaic power generation and the battery tends to be saturated, the wind power generation fails in 15:00—16:00.

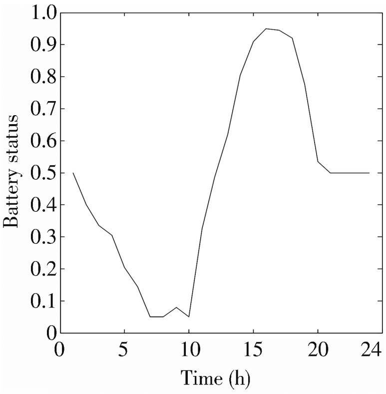

Fig. 10 Battery status

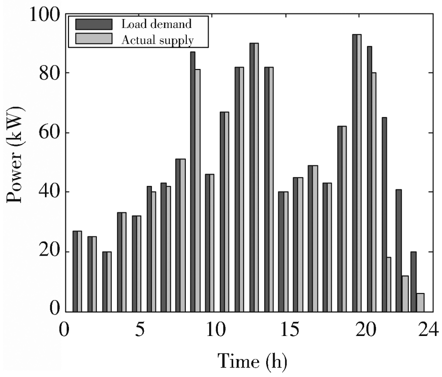

Fig. 11 Load demand and generation side supply

As shown in Fig. 10, because of the constraint that the battery initial state is equal to the end state, the battery does not discharge in 21:00—24:00. The problems of power shortage and power loss can be solved by increasing battery capacity appropriately through researching energy storage equipment, but the relationship between battery cost and power shortage-loss cost should be considered simutaneously. In addition, an incentive strategy considering multiple load types and time-of-use electricity price is proposed to improve the benefit of power generation side, consumer satisfaction and ratio of energy utilization.

Strategy 2: Considering a variety of load and time-of-use electricity price

Due to the large amount of electricity consumption from 19:00 to 22:00, the electricity cost is relatively high. The low peak period is from 13:00 to 17:00, and the electricity cost is relatively low. The electricity price of each period is shown in Fig. 12.

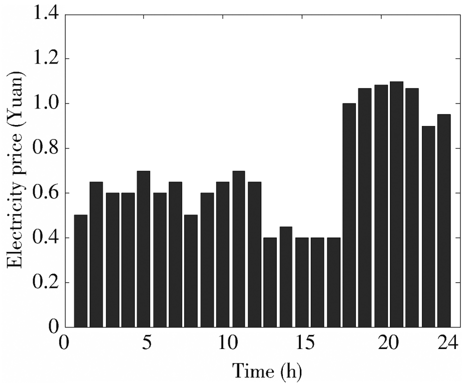

Fig. 12 Electricity price at each moment under time-of-use electricity price

When the translational load is taken into consideration, all interruptible loads can be translated. Provided that shift-out load is equal to shift-in load, it is verified by calculation that the power of generation side supply can fully meet the load demand under this condition. The comparison of supply of power schemes of strategy 1 and strategy 2 is shown in Fig. 13.

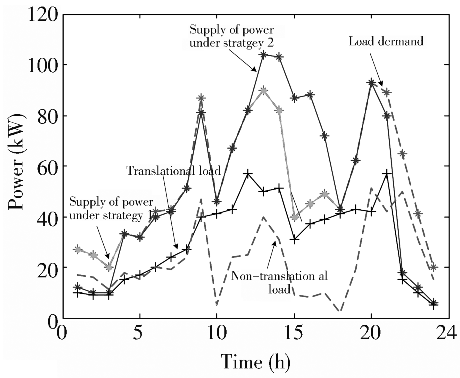

Fig. 13 Power supply schemes under different strategies

Non-translational load is indispensable to people's life. It is required that the power supply should be greater than the amount of non-translational load. The translational load represents the maximum transferable load at this moment. After translation, the load demand at a certain moment shall not be greater than the sum of the original load demand and the translational load. Under the time-of-use pricing strategy, the demand for energy storage system can be reduced by encouraging users to use electricity in low peak period. As can be seen from Fig. 13, the load is mainly shifted to the period from 12:00 to 17:00, which alleviates the pressure of power consumption during peak period and solves the problem of power loss. But at the same time the consumer's electricity comfort problem occurs, which leads to a decrease in consumer satisfaction. After taking translational load and time-of-use electricity price into consideration, the measured output power of power generation is 1 273.8 kW, which meets the load demand of users, the benefit of power generation is 667.9 Yuan, and consumer satisfaction is 92.91%.

Renewable energy efficiency and battery status are shown in Figs. 14 and 15.

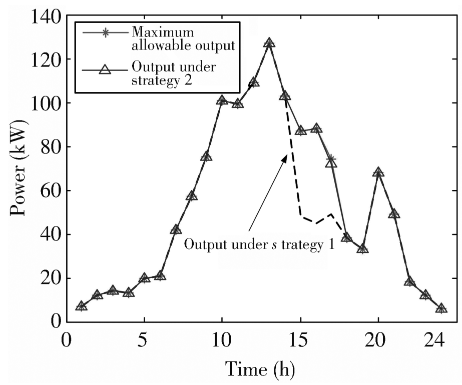

Fig. 14 Output of renewable energy

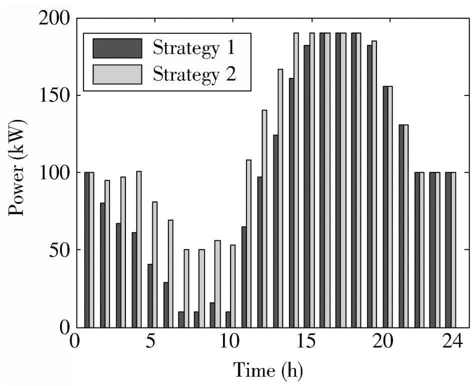

Fig. 15 Residual power of the battery

As can be seen from Figs. 14 and 15, the waste of renewable energy has been effectively solved, and the utilization rate of renewable energy has increased from 91.59% to 99.84%. In addition, the discharge depth of the battery decreases, which reduces the wastage of the battery. Strategy 1 and strategy 2 are compared in Table 4.

Table 4 Comparison of strategy 1 and strategy 2

Indicator	Benefit (Yuan)	Consumer satisfaction (%)	Power supply(kW)	Energy efficiency (%)
Strategy 1	653.2	91.50	1 167	91.59
Strategy 2	667.9	92.91	1 273.8	99.84

5 Conclusions

Micro-grid system can effectively utilize renewable distributed energy. The system optimization is an effective way to ensure the efficient operation of micro-grid system. From the perspective of energy management, the day-ahead optimization of the micro-grid system is achieved considering the maximum benefit of generation and the maximum consumer satisfaction. The proposed MO-LM-AQPSO algorithm is used to obtain the Pareto optimal solution boundary. Furthermore, the power shortage and power loss are introduced, and the optimal solution is selected to maximize the benefit of power generation. Simulation results show that the algorithm is feasible and effective. On this basis, we consider the time-of-use pricing incentive measures under various load types, and obtain the power output situation under strategy 1 and strategy 2. It is of great significance to establish the corresponding electricity price incentive measures to maximize the utilization of renewable energy and to improve the benefit of power generation and consumer satisfaction.

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兼顾用户满意度和发电侧收益的微电网系统量子粒子群优化

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摘　要： 兼顾微电网系统发电侧与用户侧的综合利益，从能量管理的角度出发，建立了以用户满意度和发电侧收益为目标的优化模型。首先，采用多目标局部变异-自适应量子粒子群算法(Multi-objective local mutation adaptive quantum particle swarm optimization，MO-LM-AQPSO)获得用户满意度及发电侧收益的Pareto前沿。然后，引入缺电损失，以发电侧收益最大为目标，选取了非支配解中的最优解，并通过算例仿真验证其有效性。进而引入可平移负荷及分时电价激励机制，通过合理的峰谷电价比以引导用户积极参与需求侧响应。仿真结果表明，合理的激励措施，可提高微电网收益和用户满意度实现可再生能源的最大化利用及蓄电池运行损耗的有效减少。

关键词： 微电网系统；用户满意度；发电侧收益；分时电价；多目标局部变异-自适应量子粒子群算法

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