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Multi-user power optimizationbased on multi-objective grey wolf Optimizer

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***Abstract*—In the smart grid environment, in order to improve the electricity habits of residential users and optimize the residential electricity structure, the idea of a home energy management system is applied to intelligent buildings. The building users and loads are classified and analyzed separately, a model of automatic demand response for building intelligent electricity scheduling is built and it is optimized for daily total electricity bill, user discomfort, and power peaks and valleys. Renewable energy, the energy storage of household electric vehicles is also considered. The multi-objective grey wolf optimization algorithm based on the fuzzy crowding judgment based on dimension review is used to solve the model. Finally, the effectiveness of the MATLAB example simulation is verified.**

Keywords—building load optimization, grey wolf optimizer, automatic demand response

I. INTRODUCTION

In the context of the current promotion of energy conservation and emission reduction, it is particularly necessary to improve residents' electricity habits and optimize the residential electricity consumption structure [1]. As an extension of the user side of the smart grid [2], intelligent buildings have the characteristics of flexible control and two-way interaction, are important carriers for optimizing the residential electricity structure. Intelligent buildings can provide strong support for stabilizing grid operation, eliminating renewable energy and satisfying users' electricity demand [3].

As a key technology for demand side management, automatic demand response(ADR) is an important way to realize grid informationization, automation and interaction [4]. home energy management(HEMS) system replaces users' response to electricity prices and makes equipment coordination optimization decisions with the support of ADR technology[5]. In [6], three types of electrical equipment are abstracted according to priority, and the effectiveness of the method is verified by experimental data. However, the priority scheduling method lacks flexibility when the number of devices is large, and the device classification is not fine enough. In [7], an optimal control method for demand response of household electricity tasks was designed in the smart grid and real-time electricity price environment, which effectively reduced the user's electricity consumption. Literature [8] proposed a hybrid particle swarm optimization algorithm based on particle correction to optimize the multi-user intelligent power consumption model of the community, which achieved a good peak-filling effect, but it lacked consideration for the user-side comfort goal.

HEMS is applied to intelligent buildings in this paper. The electrical equipment is classified and the characteristic of electrical equipment is analyzed. A model of automatic demand response for building intelligent electricity scheduling is built and it is optimized for daily total electricity bill, user discomfort, and power peaks and valleys. Renewable energy, the energy storage of household electric vehicles is also considered. The multi-objective grey wolf optimization algorithm based on the fuzzy crowding judgment based on dimension review is used to solve the model. Finally, the effectiveness of the MATLAB example simulation is verified.

II. BUILDING MULTI-USER POWER OPTIMIZATION MODELING

HEMS is a highly integrated system for comprehensive management and scheduling of household power tasks[9]. It is mainly composed of smart meters, intelligent interactive terminals, smart sockets, smart home appliances, electric vehicles, home photovoltaic systems, battery packs and other equipment. Hundreds of separate HEMSs form an intelligent building system through the connection of network communication technologies, and use ADR technology to optimize the building load.

A. Optimize the Target

The simulated power usage scenario in this paper is a common residential building. The same power company supplies power according to the charging standard of real-time electricity price. The electricity consumption data is provided by smart meters, smart sockets and intelligent interactive terminals .

Under the premise of minimizing the impact on user comfort, the purpose of rational use of electricity, energy saving and emission reduction, and stability of the power grid are achieved. The goal of optimization is composed of three items: total daily electricity bill, user discomfort, and power consumption peak-to-valley difference, and all three targets are optimized in the direction of being as small as possible. The optimization goal of mathematical expression is shown in equation (1):

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$$\min F=[C, U, D],\begin{cases} C=\sum_{i=1}^{N}\sum_{j=1}^{H}P_{i,j}c_j \\ U=\sum_{i=1}^{N}\sum_{k=1}^{K}u_{i,k} \\ D=\max_{1\le j\le H}\sum_{i=1}^{N}P_{i,j}-\min_{1\le j\le H}\sum_{i=1}^{N}P_{i,j} \end{cases} \tag{1}$$

Among them, C, U, and D respectively represent daily total electricity bill, user discomfort, and power consumption peak-to-valley difference; N is the total number of electrical loads, H means dividing 24 hours of the day into H time periods, and j means each time period; c_j is the real-time electricity price of j period, $P_{i,j}$ is the power of the jth period of load i; $u_{i,k}$ is the user's discomfort caused by the kth action of load i.

B. Restrictions

1) Interruptible load

The constraint of interruptible load is mainly from the duration of power-on and the duration of power-off, that is:

$$t\ge T_{i,min} \tag{2}$$

$$t\ge T_{i,min} \tag{3}$$

Where $T_{i,\min}$ is the shortest running time and $T'_{i,\max}$ is the longest power off time

2) Transferable load

The transferable load constraints mainly from users of its time, the load operation of the start and stop time, that is:

$$T_{j,on}\ge T_{j,onear} \tag{4}$$

$$T_{j,on}\le T_{j,onlat} \tag{5}$$

$$T_{j,off}-T_{j,on}\ge T_{j,on,std} \tag{6}$$

Among them, $T_{j,onear}$ and $T_{j,onlat}$ represent the earliest start running time and the latest start running time; $T_{j,on,std}$ represents the actual continuous working time of the load.

3) Charging load

The charging load is mainly constrained by the time of charging and discharging, that is:

$$T_{k,on}\ge T_{k,cha} \tag{7}$$

$$T_{k,off}\le T_{k,dis} \tag{8}$$

$$\mathrm{Cap}_{k,pre}+\sum_{h=T_{k,on}}^{T_{k,off}}\eta_{ch,k}X_{k,h}P_{k,h}\le Cap_k \tag{9}$$

Where $T_{k,on}$ and $T_{k,off}$ respectively indicate the start and stop times of the load k; $T_{k,cha}$ and $T_{k,dis}$ respectively indicating the load k charging start time and the charging end time; $\mathrm{Cap}_{k,pre}$ is the initial charge of the charging load k, and $\eta_{ch,k}$ is the charging efficiency of the load k; $P_{k,h}$ is the charging power of the hth period of load k, Cap_k is the maximum capacity of the battery; $X_{k,h}$ indicates whether the load k is charged in the hth period, the value is 1 when charging, and 0 when not charging.

4) Energy storage load

Energy storage load is subject to battery capacity and charge and discharge, that is:

$$Cap_{i,p}=Cap_{i,pre}+\sum_{j=1}^{p}\lambda_{ch}X_{i,j}P_{i,j}+\sum_{j=1}^{p}\lambda_{dis}X_{i,j}P_{i,j} \tag{10}$$

$$\beta_{i,max}Cap_i\ge Cap_{i,p}\ge\beta_{i,min}Cap_i \tag{11}$$

Where $Cap_{i,p}$ represents the amount of electricity of the energy storage load i during the p-th period, and $Cap_{i,pre}$ represents the amount of electricity at the zero point of the day; λ_{ch} and λ_{dis} refer to the charging efficiency and discharge efficiency of load i, respectively; $P_{i,j}$ refers to the charging and discharging power of j period, $X_{i,j}$ is the running state, the value is 1 when charging, -1 when discharging, and 0 when not charging or discharging; Cap_i is the battery capacity, $\beta_{i,max}$ and $\beta_{i,min}$ respectively indicate the maximum and minimum charge and discharge levels.

C. User Discomfort

1) Interruptible load

Interruptible load needs to complete the power-off operation at the best time that the user thinks, otherwise it will cause user rejection and user discomfort.

$$u_{i,t}=\begin{cases}1, & t<T_{i,\min}\\ \dfrac{t-T_{i,best}}{T_{i,min}-T_{i,best}}+1, & T_{i,\min}<t<T_{i,\mathrm{best}}\\ 0, & t>T_{i,best}\end{cases} \tag{12}$$

$$u'_{i,t'}=\begin{cases}0, & t'<T'_{i,\mathrm{best}}\\ \dfrac{t'-T'_{i,best}}{T'_{i,\max}-T'_{i,best}}+1, & T'_{i,\mathrm{best}}<t'<T'_{i,\max}\\ 1, & t'>T_{i,\max}\end{cases} \tag{13}$$

$$U_i=\sum u_{i,t}+\sum u'_{i,t} \tag{14}$$

Where $u_{i,t'}$ and $u'_{i,t}$ respectively represent the user discomfort generated by the interruptible load at each power-on and power-off; t and t' respectively indicate the duration of power-on and power-off; $T_{i,best}$ is the best running time; $T'_{i,best}$ indicate the best power off time; U_i indicates user discomfort generated within one day of interruptible load.

2) Transferable load

The user can freely select the operating time period within a certain time range. This type of load has a fixed running time and its running time is much shorter than the specified time range. The user discomfort calculation caused by the transferable load per run is shown in equation (15) (16):

$$u_{j,t}=\begin{cases}\dfrac{t-T_{j,best}}{T_{j,on}-T_{j,best}} & , \quad T_{j,on}<t<T_{j,\text{best}}\\ \dfrac{t-T_{j,best}}{T_{j,off}-T_{j,best}} & , \quad T_{j,\text{best}}<t<T_{j,off}\\ 1 & , \quad t<T_{j,on}\text{or}T_{j,off}<t\end{cases} \tag{15}$$

$$U_j=\Sigma u_{j,t} \tag{16}$$

Where $u_{j,t}$ represents the user discomfort generated by the transferable load; $T_{j,best}$ represents the optimal start time; $T_{j,on}$ and $T_{j,off}$ represent the load start time and end time; U_j represents the user discomfort generated within one day of the transferable load.

5) Charging load

The charging load is required to reach the predetermined capacity within the specified time, otherwise it will cause user rejection. The calculation is shown in equation (17)(18):

$$u_{k,t}=\begin{cases}1 & , \quad Cap_{k,t}<0.8Cap_k\\ \dfrac{Cap_k-Cap_{k,t}}{0.2Cap_k} & , \quad 0.8Cap_k\le Cap_{k,t}<Cap_k\\ 0 & , \quad Cap_{k,t}=Cap_k\end{cases} \tag{17}$$

$$U_k=\Sigma u_{k,t} \tag{18}$$

Where $u_{j,t}$ represents the user discomfort caused by the charging load; Cap_k represents the capacity of the charging load; $Cap_{k,t}$ represents the stored point energy during the t period; U_j represents the user discomfort generated within one day of the energy storage load.

III. Model Solution

A. Grey Wolf Optimizer

The grey wolf optimizer is a swarm intelligence optimization algorithm based on the social rank and hunting process of the grey wolf population in nature. we consider the fittest solution as the alpha(α). Consequently, the second and third best solutions are named beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω). In the GWO algorithm the hunting (optimization) is guided by α, β, and δ. The ω wolves follow these three wolves[10].The grey wolf surrounds the prey in the hunting, and the mathematical simulation of the surrounding behavior is shown in (19) (20):

$$\overline{D}=\left|\overline{C}.\overline{X_p}(t)-\overline{X}(t)\right| \tag{19}$$

$$\overline{X}(t+1)=\overline{X_p}(t)-\overline{A}.\overline{D} \tag{20}$$

Where: t represents the current iteration, $\overline{A}$ and $\overline{C}$ are coefficient vectors, $\overline{X_p}$ is the position vector of the prey, and $\overline{X}$ represents the position vector of the grey wolf.

The vectors and are calculated as follows:

$$\overline{A}=2\overline{a}.\overline{r_1}-\overline{a} \tag{21}$$

$$\overline{C}=2.\overline{r_2} \tag{22}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and $\overline{r_1}$, $\overline{r_2}$ are random vectors in [0, 1].

In order to mathematically simulate the hunting behavior of grey wolves, we suppose that the alpha (best candidate solution) beta, and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. The following formulas are proposed in this regard:

$$\overline{D_\alpha}=\left|\overline{C_1}.\overline{X_\alpha}\right|,\overline{D_\beta}=\left|\overline{C_2}.\overline{X_\beta}-\overline{X}\right|,\overline{D_\delta}=\left|\overline{C_3}.\overline{X_\delta}-\overline{X}\right| \tag{23}$$

$$\begin{cases}\overline{X_1}=\overline{X_\alpha}-\overline{A_1}.\left(\overline{D_\alpha}\right),\\ \overline{X_2}=\overline{X_\beta}-\overline{A_2}.\left(\overline{D_\beta}\right),\\ \overline{X_3}=\overline{X_\delta}-\overline{A_3}.\left(\overline{D_\delta}\right)\end{cases} \tag{24}$$

$$\overline{X}(t+1)=\frac{\overline{X_1}+\overline{X_2}+\overline{X_3}}{3} \tag{25}$$

B. Multi-target Grey Wolf Optimization Algorithm

The grey wolf optimizer was originally proposed for single-objective optimization problems. The power optimization of buildings solved in this paper is a multi-objective optimization problem with multiple optimization objectives and constraints. Therefore, the multi-target grey wolf optimization algorithm is more suitable for the current solution environment.

1) Pareto optimal

Usually for a multi-objective optimization problem with m decision variables and n optimization objectives, the mathematical relationship is expressed as equation (26):

$$\begin{cases} \min F(x) = [f_1(x), f_2(x), \cdots, f_n(x)] \\ \text{s.t. } g_i(x) \le 0, i = 1, 2, \cdots, j \\ \quad h_i(x) = 0, i = 1, 2, \cdots, k \end{cases} \tag{26}$$

Where $F(x)$ decision vector, $x = (x_1, x_2, \cdots, x_m) \in E$, E is the *m*-dimensional decision space; $g_i(x)$ is *j* inequality constraints, and $h_i(x)$ is *k* equality constraints.

The multi-objective optimization algorithm optimization process selects a group of relatively good individuals according to the individual's fitness in the population through the evolution of the population, and finally obtains the best Pareto frontier and Pareto optimal solution. The non-dominated sorting performed in non-dominated sorting genetic algorithm-II (NSGA-II) is based on the number of individuals in the population that dominate the other individuals [11]. The closer to the optimal frontier, the less the dominance is, and the stronger the dominance.

The improvement of the grey wolf optimizer in this paper is based on the Pareto correlation definition.

- Pareto dominance: For any two solution vectors $p, q \in E$, p dominate q, recorded as $p \succ q$, if and only if:

$$\begin{aligned} f_i(p) \le f_i(q), \quad \forall i \in \{1, 2, \cdots, n\} \\ f_i(p) < f_i(q), \quad \exists i \in \{1, 2, \cdots, n\} \end{aligned} \tag{27}$$

- Pareto optimal: If the solution p is Pareto optimal, if and only if: $\neg \exists q \succ p, q \in E, p \in E$.
- Pareto optimal solution set: All solutions in the set $PS = \{\mathbf{x} \mid \neg \exists \mathbf{x}^* \succ \mathbf{x},\ \mathbf{x}^*, \mathbf{x} \in E\}$ constitute the Pareto optimal solution set.
- Pareto equivalent: If two solutions $p, q \in E$ equivalent, if and only if:

$$f_i(p) = f_i(q), \quad \forall i \in \{1, 2, \cdots, n\} \tag{28}$$

In the process of algorithm optimization, several excellent equivalent individuals are very close to the Pareto front. According to the non-dominated sorting method, this cluster of excellent equivalent individuals will be eliminated in evolution, thus reducing the optimization results. According to the definition of (5) Pareto equivalence, the equivalent cluster de-duplication rule is added to the algorithm: select and retain the optimal individual in a cluster of equivalent individuals, and eliminate other individuals.

C. Crowding Judgment

Multi-objective optimization requires a relatively uniform group of non-inferior solutions in the solution space of the optimization problem. In the optimization of the frontier population distribution, this paper uses the latitude-based distance judgment rule to adopt the fuzzy crowding judgment based on dimension review.

For a multi-objective optimization problem with n targets, the optimization target is represented by an n-dimensional vector:

$$F = (f_1, f_2, \cdots, f_n) \tag{29}$$

Then the fitness distance of two different individuals a and b (the distance between the optimized target vectors) can be expressed as:

$$\begin{aligned} D_{a,b} = |F_a - F_b| = \left(D_{a,b}^1, D_{a,b}^2, \cdots, D_{a,b}^n\right) = \\ \left(|f_a^1 - f_b^1|, |f_a^2 - f_b^2|, \cdots, |f_a^n - f_b^n|\right) \end{aligned} \tag{30}$$

In a population with N individuals, the distance between a random individual a and other individuals is:

$$D_a = \begin{bmatrix} |F_a - F_1| \\ \vdots \\ |F_a - F_k| \\ \vdots \\ |F_a - F_N| \end{bmatrix} = \begin{bmatrix} |f_a^1 - f_1^1| & \cdots & |f_a^k - f_1^k| & \cdots & |f_a^n - f_1^n| \\ \vdots & \ddots & \vdots & \iddots & \\ |f_a^1 - f_k^1| & \cdots & |f_a^k - f_k^k| & \cdots & |f_a^n - f_k^n| \\ \vdots & \iddots & \vdots & \ddots & \\ |f_a^1 - f_N^1| & \cdots & |f_a^k - f_N^k| & \cdots & |f_a^n - f_N^n| \end{bmatrix}, \quad k \in [1, N], k \ne a \tag{31}$$

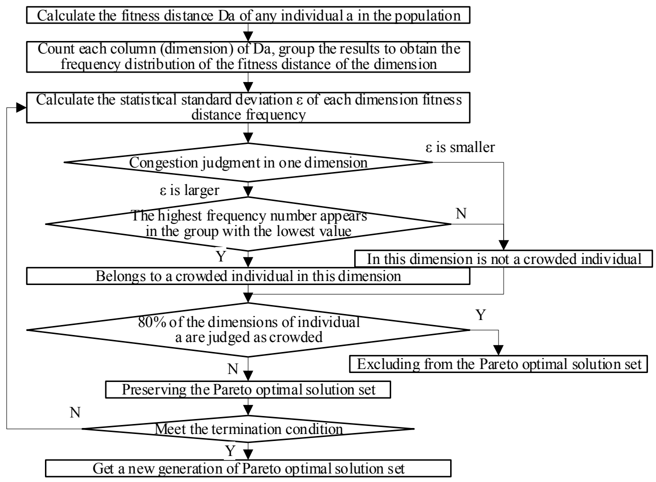


Fig. 1. The specific process of congestion determination

D. Algorithm Flow

1：System initialization, loading user load model and real-time electricity price data
2：Initialization algorithm parameter configuration, generating random initial population
3：Calculation objective function, that is individual fitness function minF＝[C，U，D]
4：Equivalent cluster deduplication
5：Non-dominated sort. After the cluster population equivalent to the weight, calculated in accordance with the number of individuals dominated Pareto optimal solution set and define the Pareto frontier, sorted by the number of levels of the Pareto frontier dominated F1, F2, F3…

6：Crowding judgment. Calculate the fuzzy crowding judgment result of the F1 optimal solution set PS1 obtained in 5, and remove the crowded individual to obtain PS1*
7：Maintain stable population number. Add PS1* to the population. If the number of individuals is less than the population size N, then add the PS2* processed by F2, and so on.
8：Calculate the fitness of each search agent
9：Update the current search agent location by equation (25)
10：Update $\vec{a}$, $\vec{A}$, and $\vec{C}$; update $\overline{X_\alpha}$, $\overline{X_\beta}$, and $\overline{X_\delta}$
11：Determine whether the termination condition is satisfied. If not, merge the generation population with the previous generation population to return 3; if satisfied, the algorithm optimization terminates, output the last generation Pareto optimal solution set and Pareto frontier

IV. Numerical Simulation and Analysis

A. *Parameter Settings*

This paper selects a typical building ADR load model with multiple types of loads and multiple types of users for analysis. There are a total of 120 users. This article divides 24 hours a day into 96 15-minute time periods, using real-time electricity price data reference [12]. The algorithm sets the population size to 600 and the number of iterations to 300.

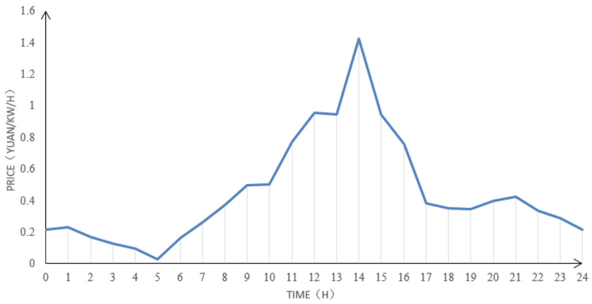
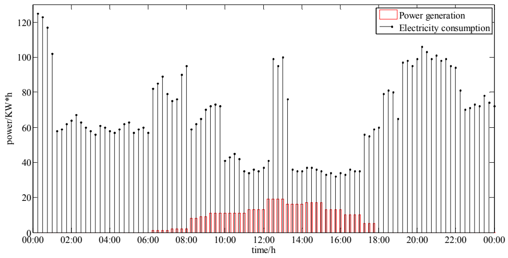


Fig. 2. Data of real-time prices

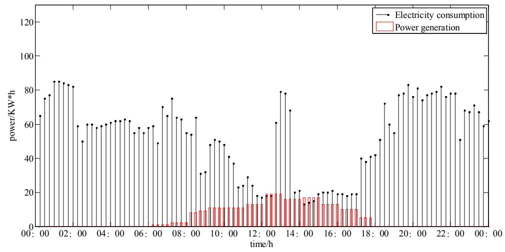
B. *Simulation Result Analysis*

Referring to the real-time electricity price curve, it can be seen from the power consumption before the building load optimization that the user mainly uses electricity according to his own electricity usage habits, and does not consider the power economy and the stability of the power system. In the peak hour of electricity price from 10 to 17 o'clock, the electricity consumption is relatively large, and the electricity consumption in the low electricity price period from 2 to 6 o'clock is small, but the user satisfaction and comfort in this electricity consumption mode are the highest.

After optimization by the multi-target grey wolf algorithm, the power consumption during the peak period of electricity price is reduced, which ensures the economical efficiency of electricity consumption; And after optimization, the electricity consumption is more uniform, and the peak-to-valley difference is reduced, which ensures the stability of the power system; Since the load usage time is changed, the user's comfort is inevitably reduced, but the user's discomfort is also minimized in the algorithm optimization.



(a)Before optimization



(b)Optimized

Fig. 3. Comparison of power consumption of building loads before and after optimization

TABLE I. Comparison of Electricity Consumption Data in Each Case

index	***Before optimization***	***Optimized***
Total daily cost /	1879.54	1029.68
User Discomfort	0	76.35
Electric power peak-to-valley difference /kW·h	94.66	79.23
Peak power consumption /kW·h	125.28	92.03

Table 1 shows the corresponding load characteristic indicators and electricity consumption costs of various methods. Under the premise of minimizing the impact on user comfort, the cost of electricity after optimization is reduced by 45%, the peak-to-valley difference of power consumption is reduced by 17.9%, and the peak value of power consumption is reduced by 27.2%.

V. Conclusion

1) According to the power characteristics of different load operation and the user's habits of different loads, this paper classifies the load into six categories and describes its characteristics. The consideration of the demand side is comprehensive, and has strong applicability.

2) Apply the idea of HEMS to intelligent buildings, and build a building electricity optimization model for the problems of electricity economy, user comfort and grid stability.

3) The multi-objective improvement of the grey wolf algorithm and the fuzzy crowding judgment based on dimension review improve the optimization speed of the algorithm and increase the population distribution. The solution to the model is expected and a set of optimal solutions is available for selection.

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