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Multi-Objective Optimization Model of Electricity Behavior Considering the Combination of Household Appliance Correlation and Comfort

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Abstract – With the wide application of intelligent household appliances, the optimization of electricity behavior has become an important component of home-based intelligent electricity. In this study, a multi-objective optimization model in an intelligent electricity environment is proposed based on economy and comfort. Firstly, the domestic consumer's load characteristics are analyzed, and the operating constraints of interruptible and transferable electrical appliances are defined. Then, constraints such as household electrical load, electricity habits, the correlation minimization electricity expenditure model of household appliances, and the comfort model of electricity use are integrated into multi-objective optimization. Finally, a continuous search multi-objective particle swarm algorithm is proposed to solve the optimization problem. The analysis of the corresponding example shows that the multi-objective optimization model can effectively reduce electricity costs and improve electricity use comfort.

Keywords: Intelligent electricity, Electricity behavior habits, Customer satisfaction, Multi-objective particle swarm optimization.

1. Introduction

With the rapid development of China's economy and improvements in people's living standards, household electricity consumption has gradually increased along with total electricity consumption nationwide, and the use of high-powered smart appliances is growing [1]. This phenomenon has created a peak in the seasonal electricity load. Meanwhile, smart grids have revolutionized electricity generation and consumption via a two-way flow of power and information [2]. On one hand, this flow helps the grid to expand integrated services for users; on the other, it is necessary to examine users' electricity habits via analysis [3, 4] to adjust electricity service, help users improve efficiency, and optimize electricity use. Therefore, power users are becoming increasingly important in demand-side management. The focus of this paper is to rationally arrange and optimize household smart electricity behavior to effectively reduce electricity costs with the aim of ensuring the user's electricity comfort .

Currently, countries around the world have set aggressive goals to optimize smart electricity behavior in liberalized markets, especially on the demand side. By dividing a day into slots based on starting time, the length of operation and electricity consumption in each slot (including electricity consumption characteristics and pricing mechanisms), we propose an intelligent electricity consumption optimization approach to minimize electricity consumption fees [5]. [6] reviewed the concept of energy management systems for residential customers and explored the background of smart home energy management system technologies. Meanwhile, studies have proposed an optimal and automatic residential energy consumption scheduling framework that attempts to achieve a desired trade-off between minimizing electricity payments and minimizing waiting times for the operation of each appliance in the household given a real-time pricing tariff and increasing block rates [7]. In addition, demand-side management encourages users in a smart grid to shift their electricity consumption in response to fluctuating electricity prices. A distributed framework is proposed for the demand response based on cost minimization; this optimization method will result in lower costs for consumers, lower generation costs for utility companies, lower peak load, and lower load fluctuations [8, 9]. Mohsenian-Radet al. [10] outlined an optimization framework that aims to minimize electricity bills while considering user comfort; however, the assumption of homogeneous appliances and using waiting time to represent user comfort would be too simplistic in this paper to represent different characteristics of home appliances and user requirements. RohH T al. [11] studied an electricity load scheduling problem in a residence. Compared with previous works in which only

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limited sets of appliances were considered, the authors categorized various appliances into five sets based on varying energy consumption and operation characteristics and provided accompanying mathematical models.

In fact, to the best of our knowledge, none of the prior work on residential load control has considered household appliance correlations and comfort on the user side. Recently, more attention has been paid to the role of demand response (DR) to time-varying pricing such astime-of-use (TOU) pricing [12-14]. In the TOU price environment,the contributions of this paper are as follows:The contributions of this paper are as follows:

1) Given the constraints of controlled electrical appliances and proposed concept of household electricity load correlation, we construct a minimum electricity expenditure model based on household electricity load correlation.

2) With the objective of minimizing changes in electricity habits, the model is constructed with an emphasis on user satisfaction.

3) A multi-objective optimization model is proposed in the intelligent electricity environment with dual focuses on economy and comfort.

4) Continued research regarding the multi-objective particle algorithm is proposed to solve the optimization problem. Specifically, the model can achieve significant savings in electricity costs, more flexibility in the trade-off between cost and user comfort, and reduced energy demand during peak hours.

The rest of this paper is organized as follows. We introduce the residential electricity load and notations in Section II. In Section III, we construct the multi-objective optimization model, which includes a minimum electricity expenditure model considering household electricity load correlation and user comfort. Our proposed continuous search of multi-objective particle swarm optimization (CSMOPSO) appears in Section IV. The simulation experiment is explained and results are provided and discussed in Section V. Finally, conclusions are drawn in Section VI.

2. Analysis of Residential Electricity Load

According to customary user power consumption and household appliances' operational characteristics, the load of household electric appliances can be divided into three types: base load, interruptible load, and transferable load. The base load can neither change the power of a task nor optimize electricity use, as in refrigerators, lights, and so on. The interruptible load and transferable load can dispatch the power utilization task for a period of time as long as the user can complete the designated power consumption task, such as with air conditioning, washing machines, etc. Because the optimization of power consumption behavior does not affect the power consumption of the base load, this paper only establishes operating constraints for the interruptible load and transferable load and analyzes power consumption optimization.

2.1 Interruptible load

The working range of the interruptible load i is [$a_{IL,i}$, $b_{IL,i}$], and each working period is β. Before completing a power consumption task, users can use electrical appliances according to their habits.

$$L_{\mathrm{IL},i}(t)=\sum_{t=a_{IL,i}}^{b_{IL,i}} p_{\mathrm{IL},i}(t)l_{\mathrm{IL},i}(t) \tag{1}$$

where

$$l_{\mathrm{IL},i}(t)=\begin{cases}1, i \ is\ running\\ 0, otherwise\end{cases} \tag{2}$$

$$a_{IL,ei} \le a_{IL,i} \le a_{IL,li} \tag{3}$$

$$\sum_{t=t_1}^{t_1+\beta} l_{\mathrm{IL},i}(t)=\beta l_{\mathrm{IL},i}(t) \tag{4}$$

where $p_{IL,i}(t)$ is the power of the appliancel i; $l_{IL,i}(t)$ indicates the use state of the interruptible load (when the interruptible load is running, the $l_{IL,i}(t)$ is 1; otherwise, its value is 0); $L_{IL,i}$(t) is the total power of i; β is the last working time of the interruptible load; $a_{IL,ei}$ is the earliest time to open interruptible load i for the user; and $a_{IL,li}$ is the latest time to open interruptible load i for the user.

The total power consumption is the sum of all interruptible electrical appliances, as shown in Eq. (5):

$$L_{\mathrm{IL}}(t)=\sum_{i=1}^{m} L_{\mathrm{IL},i}(t) \tag{5}$$

where m is the total number of interruptible appliances.

2.2 Transferable load

According to the user's power habits, it can be concluded that the working range of the transferable load i is [$a_{TL,i}$,$b_{TL,i}$]. The running time of the non-stop electrical appliance is continuous and can be stopped only when the task is completed.The total electricity is shown in Eq. (6):

$$L_{\mathrm{TL},i}(t)=\sum_{t=a_{TL,i}}^{b_{TL,i}} p_{\mathrm{TL},i}(t)l_{\mathrm{TL},i}(t) \tag{6}$$

where

$$l_{\mathrm{TL},i}(t)p_{TL,i}^{\min}(t) \le p_{TL,i}(t) \le l_{\mathrm{TL},i}(t)p_{TL,i}^{\max}(t) \tag{7}$$

$$\sum_{t=t}^{t+(M-1)} l_{TL,i}(t) \ge M\left|l_{TL,i}(t)-l_{TL,i}(t-1)\right| \tag{8}$$

$$a_{TL,ei} \le a_{TL,i} \le a_{TL,li} \tag{9}$$

where $p_{TL,i}(t)$ is the power of the appliance i; $l_{TL,i}(t)$

indicates the use state of the transferable load; $L_{IL,i}(t)$ is the total power of i; and M represents the number of working hours of i. $p_{TL,i}^{\min}(t)$ and $p_{TL,i}^{\max}(t)$ are the minimum and maximum values of the transferable load's power; $a_{TL,ei}$ is the earliest time to open transferable load i for the user; and $a_{TL,li}$ is the latest time to open transferable load i for the user. Eq. (8) shows that transferable load i runs continuously from time t at runtime.

In addition, electric vehicles and batteries are generally considered part of household smart electricity and can be adjusted for use time according to their condition. The constraints are as follows:

$$Q_{TL,i}(t) = Q_{TL,i}(t-1) + \mu p_{TL,i}(t) \tag{10}$$

$$Q_{\min} \le Q_{TL,i}(t) \le Q_{\max} \tag{11}$$

$$Q_{TL,i}(b_{TL,i}) = Q_{TL,i}^{d} \tag{12}$$

where $Q_{TL,i}(t)$ is the electricity of the charging and discharging equipment, and μ is the efficiency of charging and discharging. Other parameters, denoted as Q_{min} and Q_{max}, represent the range of the electricity; $Q_{TL,i}^{d}$ is the amount of electricity required to complete the task.

The total power consumption is the sum of all transferable loads as shown in Eq. (13).

$$L_{\mathrm{TL}}(t) = \sum_{i=1}^{n} L_{\mathrm{TL},i}(t) \tag{13}$$

where n is the total number of transferable loads.

3. Multi-Objective Optimization Model for Electrical Behavior

The multi-objective optimization model in the intelligent electricity environment is proposed based on economy and comfort.

3.1 The minimum electricity expenditure model considering household electricity load correlation

The electricity cost of household intelligent electricity is the total power consumption of three kinds of household appliances, which are the base load, interruptible load, and transferable load. According to the actual use of each household appliance, the objective of the electricity cost function is to complete the user's electricity consumption task while keeping electricity costs to a minimum. Therefore, we denote the cost function as

$$\min \mathrm{Cos}\,t = \sum_{t=1}^{24} C(t)(L_{IL}(t) + L_{TL}(t)) \tag{14}$$

where

$$\sum_{t=1}^{24} (L_{IL}(t) + L_{TL}(t)) \le U_{\max} - U_{\text{uncontrollable}} \tag{15}$$

$$a_{ei} \le a_i \le a_{li} \tag{16}$$

where the underlying parameters are represented thusly: $C(t)(t=1,2,3...,24)$ is the TOU price; a_{ei} is the earliest time to open i for the user; a_{lt} is the latest time to open i for the user; U_{max} is the maximum capacity for home lines; and $U_{uncontrollable}$ is the total power of uncontrolled household appliances during this working period. Eq. (15) shows all appliances' total electric power limit. Eq. (16) indicates the actual opening time of i in the permissible opening time of the users.

In light of the huge uncertainty in demand response of household loads, this paper suggests that cooperative use of household electrical appliances is an important factor affecting household users' response; thus, we propose the concept of household electricity load correlation in which we construct a household electricity load model and design a real-time updated optimization strategy based on household electricity load correlation.

The household electricity load correlation represents the use of the appliance in conjunction with others. According to the use time of each household appliance, we establish a matrix to represent the correlation of electrical appliances [15]. The matrices are as follows (17):

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1i} \\ r_{21} & r_{22} & \cdots & r_{2i} \\ \vdots & \vdots & \ddots & \vdots \\ r_{i1} & r_{i2} & \cdots & r_{ii} \end{bmatrix} \tag{17}$$

where $r_{ij} \in [0,1]$. If $r_{ij}=1$, the appliances i and j are used at the same time, and if $r_{ij}=0$, home appliances i and j are used separately. The underlying coefficients are denoted as (18):

$$\begin{cases} r_{ij} = \dfrac{\min(b_i,b_j) - \max(a_i,a_j)}{\max(b_i,b_j) - \min(a_i,a_j)}, \min(b_i,b_j) \ge \max(a_i,a_j) \\ r_{ij} = 0, \min(b_i,b_j) < \max(a_i,a_j) \end{cases} \tag{18}$$

Using r_{ij} to modify the parameters of a_{ei} and a_{lt} in the formula (16). In this way, the model takes into account the user's power consumption habits and avoids confusion when optimizing the use of existing home appliances.

$$a_{ei} = f(r_{ij}a_{ej}) = \frac{\sum_{j=(1,n)} r_{ij}^{\,6} a_{ej}}{\sum_{j=(1,n)} r_{ij}^{\,6}} \tag{19}$$

$$a_{li} = f(r_{ij}a_{lj}) = \frac{\sum_{j=(1,n)} r_{ij}^{\,6} a_{lj}}{\sum_{j=(1,n)} r_{ij}^{\,6}} \tag{20}$$

3.2 User electricity comfort model

When the optimization of the original behavior requires more adjustment, user comfort is low. In other words, the longer the running time of an appliance, the lower the user's comfort level before and after optimization. The user's electricity comfort model is as follows:

$$\max Comfort = 1 - \frac{\sum_{i=1}^{m+n}\sum_{t=1}^{24} p_i(t)\left|l_i^0(t) - l_i(t)\right|}{\sum_{i=1}^{m+n}\sum_{t=1}^{24} p_i^0(t) l_i^0(t)} \tag{21}$$

where

$$\sum_{t=1}^{24} l_i(t) = \sum_{t=1}^{24} l_i^0(t) \tag{22}$$

where $p_i^0(t)$ and $p_i(t)$ are the original and optimized electricity power; $l_i^0(t)$ and l_i are the original and optimized power consumption plans; and η_i is the coefficient of i that cannot be adjusted.

3.3 Multi-objective optimization model

The model consists of two parts. The first part is the total electricity cost, which can be expressed as (14). The objective of this function is to adjust the home appliance plan to lower the TOU price. The second part of the objective function is the comfort cost, which can satisfy the user's electrical habits. These two objective functions are inherently contradictory, hence our proposal of a multi-objective optimization model of electrical behavior that considers the correlation and comfort of electrical appliances. The model is as follows:

$$\min F = \begin{cases} \min Cost \\ \max Comfort \end{cases} \tag{23}$$

where *Cost* is (14) and *Comfort* is (21).

4. Continuous Search of Multi-Objective Particle Swarm Optimization

Particle swarm optimization (PSO) is a relatively recent heuristic inspired by the choreography of a bird flock. It is a population-based stochastic optimization method developed by Eberhart and Kennedy. The algorithm is simple yet powerful [16]. PSO adapts behavior representing the global optimum and looks for the best solution vector in the search space [17]. Despite its current success in diverse optimization tasks, PSO remains one of the heuristics for which limited research on multi-objective optimization has been conducted. PSO has been successfully used for continuous nonlinear and discrete binary single-objective optimization and seems particularly suitable for multi-objective optimization, mainly because of the algorithm's high-speed convergence in single-objective optimization. Multi-objective particle swarm optimization (MOPSO) allows the PSO algorithm to manage multi-objective optimization problems [18].

A variant of MOPSO, termed CSMOPSO, is proposed in this paper. We add the function factor on the random velocity operator, the inertia weight, and other original parameters to design a continuous search of multi-objective particle swarm optimization (CSMOPSO) to solve the model.

4.1 Particle swarm optimization

We can compute the speed and position of each particle using the following expression:

$$V_i(t+1) = wV_i(t) + c_1 r_1 (P_{best} - X_i(t)) + c_2 r_2 (G_{best} - X_i(t)) \tag{24}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{25}$$

where w is the inertia weight; r_1 and r_2 are random numbers in the range [0,1]; P_{best} is the best position the particle has had; G_{best} is a value taken from the repository; and c_1 and c_2 (learning factor) have a value of 2.0.

4.2 Continuous search of multi-objective particle swarm optimization

MOPSO solves the optimization problem of multiple target constraints, which is generated in the basic algorithm of multiple solutions in the selection of an optimal solution set (i.e., the set of Pareto optimal solutions). To prevent the algorithm into a local optimum, we have improved the MOPSO algorithm:

4.2.1 Select strategy inertia weight w

To achieve a balance between the global search and local search, the value of w is calculated using a dynamic decreasing method.

$$w(t) = 0.8 * e^{-\frac{t}{\max}} + 0.1 \tag{26}$$

where *max* is the maximum number of iterations.

4.2.2 Increase random velocity operator

To ensure continuous searching of particles in the algorithm and to make prevention of a local optimum more likely, the formula of the speed update in (24) (25) will be improved, and a random velocity operator will be introduced.

$$V_i(t+1) = wV_i(t) + c_1r_1(P_{best} - X_i(t)) + c_2r_2(G_{best} - X_i(t)) + a(t/T_{\max})^2 + b(t/T_{\max}) \quad (27)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (28)$$

where a, b are very small random numbers with respective values of (0.001, 0.01).

4.2.3 Calculate intensive distance

The number of targets to be optimized for electricity behavior is 2, so the intensive distance of particle Xi can be depicted as follows:

$$D(X_i) = \sum_{n=1}^{2} \left| f_n(X_j) - f_n(X_k) \right| / f_{\max} \quad (29)$$

In the formula, $f_n(X_i)$ is the n objective function value of X_i, and f_{max} is the maximum value of the external document.

4.2.4 Determine and update P_{best}

The first step is to make sure the initial position of particle i is P_{best}. If the iteration position of i in t times is P_{best} dominated by X_i, then the updated individual optimization is X_i; otherwise, the individual optimal value is the highest number of selected dominant particles.

4.2.5 Determine and update G_{best}

We apply the optimal Pareto solution for particles in the external document. By using (27) (28), the initial position of the particle P_{best} and the top particle position G_{best} is found, then the optimal solution of Pareto is found, and (29) is used to obtain the intensive distance, which is sorted in descending order; finally, G_{best} is selected.

The algorithm of CSMOPSO is as follows:

(a) Initialization. We enter the initialization parameters of time and power for each home appliance. The particle size is the number of home appliances, the size of the group is S, each individual particle corresponds to home appliances' scheduling plan, and to ensure that the solution of particles is optimal in day 24;

(b) Determine the objective function. The individual particles are entered as variables into the model, the external document is initialized, and the initial value of the Pareto optimal solution is placed. Then,

(c) According to the updated formula for the particles' velocity and position (i.e., as determined by (27) (28)), the dynamic inertia weight is set. Next, we

(d) Update the A and P_{best} of particle populations according to the preceding rules;

(e) Re-update the Pareto optimal solution and re-input A to determine whether the number of solutions exceeds the capacity; if so, we update and cut it according to the intensive distance and find G_{best}.

(f) If it meets the mutation requirements at this time, we randomly select a particle and let it achieve random variation, then implement the mutation operations;

(g) If the number of iterations $t = t+1$, return to step c) and continue to run until $t \geqq max;$

(h) Once the iteration is terminated and the optimal position of each dimensional particle is obtained, we have the optimal opening time, $l_{i,t}$, for each appliance.

The algorithm flow is shown in Fig. 1.

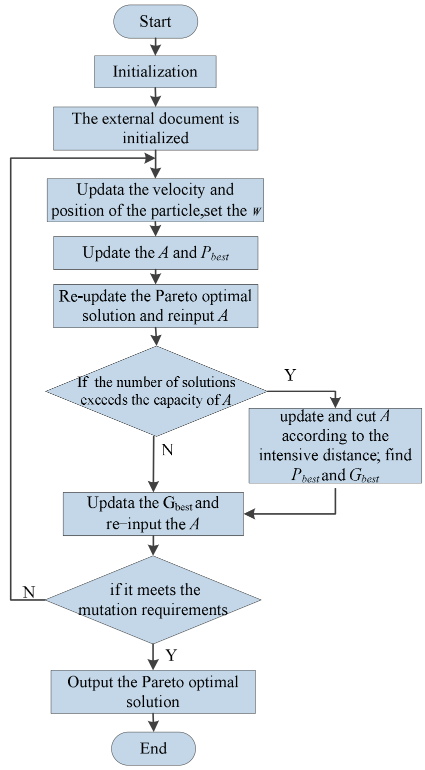

Fig. 1. Flowchart of the proposed algorithm

5. Simulation Experiment and Analysis

5.1 Experimental comparison and analysis of MOPSO

FON was proposed by Click in 1999. The standard test function selected in this paper is a commonly used test function in MOPSO, as shown in Eq. (30).

$$FON = \begin{cases} \min f_1(x) = 1 - \exp(-\sum_{i=1}^{n_k} (x_i - 1/\sqrt{3})^2) \\ \min f_2(x) = 1 - \exp(-\sum_{i=1}^{n_k} (x_i + 1/\sqrt{3})^2) \end{cases} \quad (30)$$

where n_k is the dimension of decision variables and equal to 3.

From Fig. 2 and Fig. 3, it is apparent that both the improved and unmodified MOPSO converge well to the

Table 1 GD evaluation index data

GD	Best	Worst	Mean	Median	Std
MOPSO	0.0002	0.0028	0.0015	4.1586e-04	4.6958e-04
CSMOPSO	0.0005	0.0027	0.0016	2.1722e-04	3.7534e-04

Table 2 SP evaluation index data

SP	Best	Worst	Mean	Median	Std
MOPSO	0.00083	0.0123	0.0066	0.0059	0.0033
CSMOPSO	0.00064	0.0105	0.0056	0.0045	0.0026

Table 3. ER evaluation index data

ER	Best	Worst	Mean	Median	Std
MOPSO	0.0013	0.0865	0.0439	0.0324	0.0178
CSMOPSO	0.0009	0.0762	0.0386	0.0310	0.0158

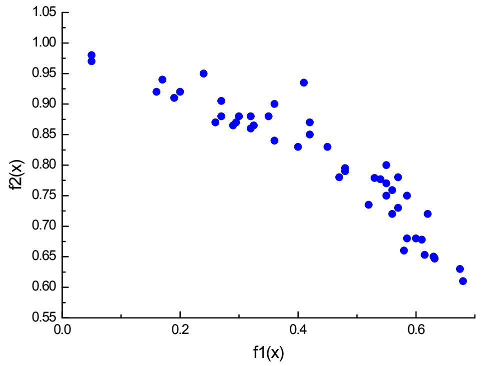

Fig. 2 Pareto front-end diagram of the unmodified algorithm

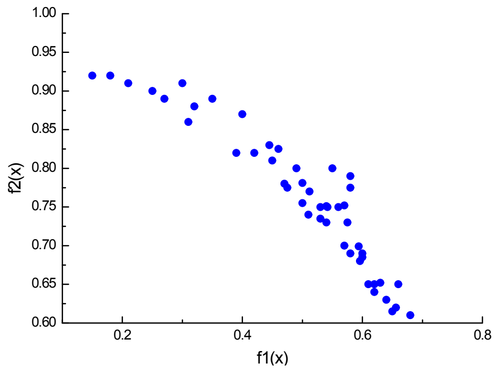

Fig. 3. Pareto front-end diagram of the improved algorithm

Pareto optimal front-end; therefore, we can judge the quality of the modification before and after the improvement from three angles: specific data of diversity, distribution, and error ratio.

The following specific comparison focuses on the experimental data from the design evaluation method. The two algorithms, which are presented in Tables 1, 2, and 3, provide three aspects for comparison: the convergence of the indicators, the diversity index, and the error ratio. The algorithm was run 30 times and the results were averaged.

As can be seen from Tables 1, when the same test function FON is applied, the same parameters are selected. The CSMOPSO algorithm does not show much improvement on convergence performance compared with the unmodified one

As can be seen from Tables 2, when the same test function FON is applied, the same parameters are selected. The diversity index increased by about 15%.

As can be seen from Tables 2, when the same test function FON is applied, the same parameters are selected. The error ratio increased by an average of 12.1%.

5.2 Experimental data sets and processing

5.2.1 Experimental data sets

The data of the simulation experiment were composed of power data from an intelligent district published by UCI database [19] and contained user information and total power consumption peaks and valleys. In addition, there were 3 smart meters for household data, including in the kitchen, laundry room, living room, and bedroom.

As shown in Table 4, the TOU price environment is divided into four grades (low, flat, peak, and peak), which is the basis for the study.

Table 4. Time-sharing electricity prices in Guangdong province

Type	Price period	Price/(￥/KW·h)
Low price	0:00 - 7:00 22:00 - 24:00	0.208
Flat section price	7:00 - 11:00 14:00 - 18:00	0.52
Peak price	11:00 - 14:00 18:00 - 22:00	0.832

5.2.2 Dataset processing

The power consumption data of intelligent residential districts were clustered using a K-means algorithm, and four kinds of users with different power usage were obtained (see Fig. 4). After analyzing and summarizing the results, we obtained behavior characteristics of all users, as shown in Table 5.

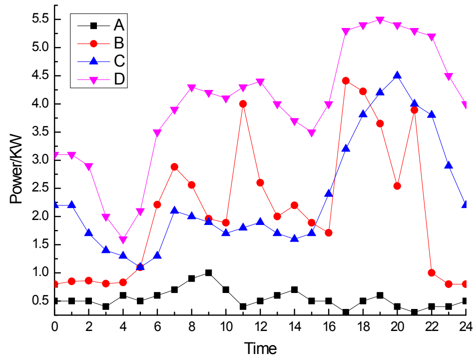

Fig. 4. Classification of residents' behavior habits

Table 5. The user behavior characteristics

Category	Name	Features	Electric appliances
A	Low power users	These users have fewer family members and lower power consumption and peak and valley power; there are almost no high-powered appliances in the home	6
B	Elderly family	Electricity consumption remains high during the day and begins to rise at 13 before declining early in the evening; high-powered appliances are relatively few	12
C	Office worker	Electricity consumption has obvious peaks and valleys; electricity is higher at night than during the day; compared to the B class, the decline in electricity consumption is time delayed	15
D	Elderly and office worker family	A larger number of family members; total electricity consumption, peak, and low power continue to be high	17

In view of the different types of households, the electricity consumption plan is independent which obtained by using the electricity optimization model. Therefore, this paper used the B electricity data to carry out the example analysis. Three different smart meters could be used to obtain different appliances' electrical behavior. We selected the basic power consumption data for nine types of household appliances to analyze their power consumption behavior: microwave oven, range hood, induction cooker, dishwasher, rice cooker, washing machine, calorifier, athroommaster, and air conditioning.

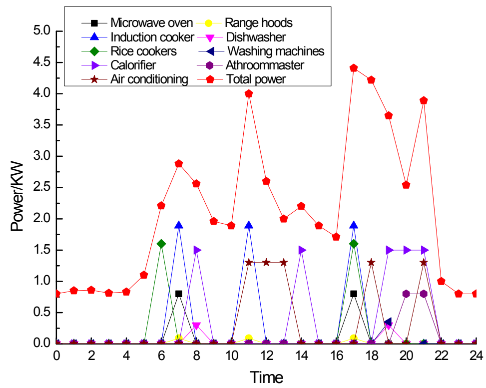

Fig. 5. The power consumption plan aimed at users' comfort

5.3 Example analysis of optimization model

To solve problems with the model, we propose CSMOPSO in this paper. The relevant parameters are as follows: the population size S is 100; the maximum capacity P of A is 100; the mutation probability is $P_m = 0.2$; $max = 150$; $c_1 = c_2 = 2$; and $w = 0.8$.

The optimization of the electricity consumption plan can be divided into the following four cases:

5.3.1 Users' electricity comfort

Considering the user's electricity comfort, electricity behavior was optimized to get the optimized electricity plan; results appear in Fig. 5.

The optimization results show that the user's electrical behavior was unchanged when optimizing power consumption with the aim of maintaining users' electrical comfort. Compared with Fig. 4, Fig. 5 shows that the electricity plan is the user's original electricity usage. At this time, the electrical comfort is highest; therefore, the cost of the original electricity is ￥16.71.

As indicated by the optimization results in Fig. 5 (i.e., the original electricity consumption plan), the other three cases were compared with this case.

5.3.2 Minimum electricity cost as the target

Only considering the economy, the optimized electricity plan can be obtained by the minimum electricity expenditure model. The results of this experiment are shown in Fig. 6.

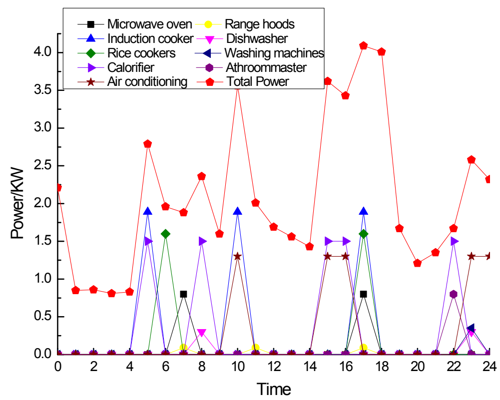

Fig. 6. The power consumption plan aimed at minimizing electricity costs

Compared with Fig. 5, the electricity plan for household appliances was adjusted to the lowest point or the flat section of the TOU tariff, where electricity costs were at least 32.23% less than originally planned (i.e., the electricity cost is ￥11.35). However, the user's consumption habits show substantial changes, such as the electromagnetic oven plan changing from 7 points to 5 points; the air conditioner being used at 24 points; and some appliances used in conjunction with the time were staggering. The satisfaction of the optimization result was lowest in this context and conformed to the user's habits.

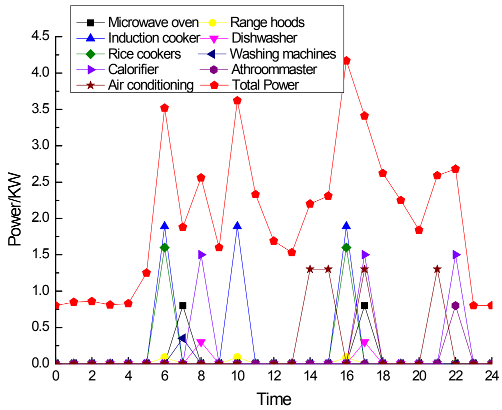

Fig. 7. Power consumption plan aimed at minimizing the cost of household electricity load correlation

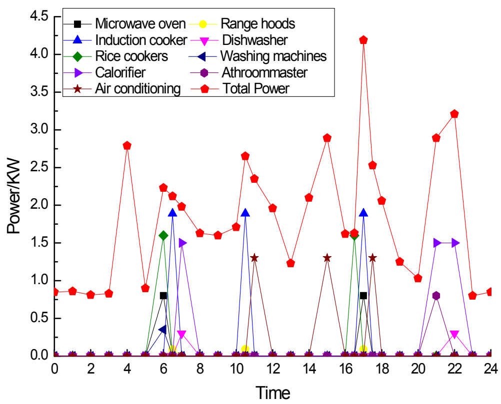

Fig. 8. Power consumption plan for multi-objective optimization model

5.3.3 Aim to minimize the cost of household electricity load correlation

According to the matrix of the household electricity load correlation, the parameters of the tariff model were corrected by the correlation coefficient. The results of this experiment are displayed in Fig. 7.

As shown in Fig. 7, these appliances can be adjusted at the same time to allow for cooperative household use, such as with the range hood and induction cooker, dishwasher and calorifier, etc. The electricity cost was ￥14.58 at this time, 12.74% less than the original plan. Compared with Fig. 5, the plans of associated home appliances changed simultaneously, so the user's electrical comfort was affected. In addition, a new peak was generated.

5.3.4 Multi-objective optimization model

The results of the multi-objective optimization model are shown in Fig. 8.

The simulation results show that the proposed multi-objective optimization model can realize the comprehendsive consideration of cost and comfort, especially the influence of the household electricity load correlation. In this case, the electricity cost was ￥13.63, less than the original plan and reduced by 18.43%.

Finally, the optimization results of the four cases were compared and analyzed. The results are shown in Fig. 9 and Table 6.

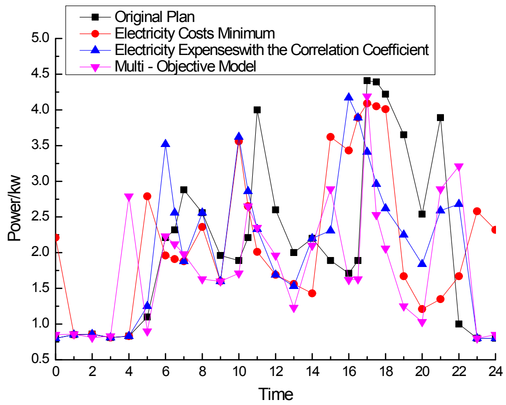

Fig. 9. Comparison of power consumption before and after optimization

Table 6. Optimization results of different modes

Optimization stage	Comfort	Economy	Cost/￥	Total satisfaction
1	1.00	1.00	16.71	1.00
2	0.34	1.67	11.35	0.56
3	0.63	1.26	14.58	0.79
4	0.76	1.53	13.63	1.16

From the results in Fig. 9 and Table 6, we can see that the multi-objective model significantly outperformed the others in terms of reducing energy costs. If the optimization of power consumption is carried out with a single objective, the optimum of the single target can only be achieved, and other targets will be affected accordingly.

6. Conclusion

In a time-sharing electricity environment, starting with the user's electricity habits and combined with costs, we have proposed a multi-objective optimization model of electricity behavior to jointly optimize the household appliance correlation and home energy scheduling with a focus on user comfort. The CSMOPSO algorithm was proposed to solve the optimization problem. By comparing electrical behavior optimization under four conditions, we found the proposed model for residential electricity consumption behavior analysis to be accurate and effective: the multi-objective optimization model can effectively reduce the cost of electricity and improve user comfort.

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