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Optimizing home electricity consumption with user habits analysis

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With the development of the national economy and the advancement of urbanization, the demand for household electricity consumption is rising sharply and the structure of the complexity of the trend. In order to help users realize intelligent management of household electricity consumption and improve the efficiency of electricity consumption. This paper proposes a smart home electricity consumption optimization method based on user habit analysis. Firstly, the home energy management system framework and related technologies are introduced, and home load dispatch types are categorized and modeled. Then, a circular coordinate fitting method is used to analyze the data and thus derive the users' electricity consumption habits, as well as an improved K-mean clustering algorithm to mine the users' personalized demands. Then, a multi-objective intelligent power consumption optimization model is established, and an improved artificial bee colony algorithm is used to solve practical problems. Finally, simulation experiments using real household electricity consumption datasets are conducted to verify the validity and feasibility of the method. The method in this paper can formulate power consumption plans according to the needs of different families, improve the convenience and comfort of users' power consumption, and realize more reasonable and energy-saving power consumption through users' participation in adjusting and improving their habitual behaviors. This research has application value and promotion significance and can be widely used in the field of smart home and energy saving and emission reduction.

Key words: household electricity optimization, user habits, multi-objective optimization, k-mean clustering algorithm, artificial bee colony algorithm

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1. Introduction

In recent years, with the rapid development of the economy and science and technology, the scale of various industries has been expanding, and the demand for electricity has also grown. As an efficient and clean energy source, electricity plays an important role in promoting social development. Among the continuous rise in electricity demand, the electricity consumption of domestic households has grown most rapidly. Therefore, electricity has become an indispensable energy source in modern society and is of great significance to the lives of residents. However, as the demand for electricity grows, the popularization of high-power smart electrical appliances and household electric vehicles has brought about a series of problems, such as insufficient power supply, insufficient energy and low energy utilization. In addition, the popularity of renewable energy systems such as photovoltaic power generation and wind power generation has made home energy management systems increasingly complex, and traditional energy management with imperfect communication and relying only on user awareness is no longer able to solve the current energy and environmental problems. However, the rapid development of smart electricity technology and the reform and innovation of the electricity market provide new opportunities and challenges for energy management research. In this context, the study of intelligent management of residential electricity consumption is of great significance. By providing an optimal decision-making scheme for household electricity consumption, we can improve the quality of electricity consumption, efficiency of electricity consumption and the ability to save energy of residents and achieve a balance between supply and demand. This not only meets people's needs for automation and intelligent life at the same time but also responds to the social development trend of energy efficiency and low carbon economy, bringing important economic, environmental and social benefits.

Many optimization methods have emerged in the field of home electricity optimization. Smart grids [1] have emerged to improve the efficiency of electricity production, distribution and transmission, and to compensate for the shortcomings of traditional grids. Smart electricity technology has been applied in home energy management to reduce electricity expenses and balance electricity demand. Related studies include electricity consumption data analysis [2,3], energy consumption monitoring [4,5] and remote control [6–8]. Research scholars have conducted numerous studies on home energy management systems [9], including optimized scheduling strategies [10], information interaction [11], and power load scheduling [12]. These studies are important for improving the efficiency of household electricity consumption and reducing costs.

Electricity demand side management is an important part of power system planning and operation. Through intelligent power consumption behavior and optimization strategies, it can improve users' motivation to use electricity, optimize energy consumption, reduce the burden on the power grid, and tap demand-side potential. Research scholars have proposed a variety of household energy optimization strategies, such as using machine learning techniques for electricity price prediction and price clustering [13–15], establishing appropriate rules to reduce power peaks [16], and introducing cost optimization algorithms to control the usage of dispatchable devices [17–20]. Significant progress has also been made in energy storage systems [21] and distributed power supply optimization [22], such as shifting electrical loads from the grid to solar power through a monitoring system [23, 24], and maximizing renewable energy utilization by managing the timing of battery charging and discharging [25, 26]. These studies can effectively reduce energy consumption, improve user comfort and economic benefits.

The analysis of users' electricity consumption habits can provide powerful help for demand-side electricity consumption optimization schemes. The wide application of smart meters makes it easy and convenient to collect electricity consumption data. At present, data mining techniques are mainly used for user classification and electricity consumption habit analysis. Research scholars have conducted extensive studies. For example, a method for analyzing users' electricity consumption behavior for smart electricity environment [27], a comprehensive clustering method for analyzing users' weekly electricity consumption data and giving suggestions [28] and predicting household users' electricity consumption using smart meter data [29].

However, intelligent electricity consumption data mining still faces difficulties such as large data volume, high dimensionality, low mining efficiency, etc. How to improve the clustering results and algorithmic efficiency of user behavior clustering research is also a research hotspot in this field. The K-mean clustering algorithm has been widely used in the research of user electricity usage habit analysis. However, many users lack the appropriate skills and experience. The parameter setting is on the side of theorizing and has a single objective. At the same time, intelligent algorithms also have shortcomings such as easy falling into local optimization and slow convergence. For these problems, further research and exploration are needed. To solve the above problems, this paper adopts a circular coordinate fitting method to analyze the user's electricity habits and applies an improved K-mean clustering algorithm to mine the user's personalized demand for home appliances. Next, a multi-objective intelligent power usage optimization model is established, and an improved artificial bee colony algorithm is introduced to solve the practical problems. Through these studies, this paper aims to increase user participation, enable personalized parameter settings, and improve the performance of the intelligent algorithm. Optimized scheduling through home energy management systems can reduce energy consumption, decrease energy costs, and improve home energy efficiency. This study not only fills the research gap in home electricity optimization but also provides a valuable reference for future research on home electricity optimization.

2. Home energy management system and electricity load modeling

The home energy management system is a prerequisite for the optimal scheduling of home loads, and it allows for the integrated management of home power loads and distributed energy sources. By collecting data such as indoor environment and operating status of household equipment through intelligent sensing facilities, and combining it with dynamic tariffs and user feedback, the home energy management system can quickly come up with a solution and send the control action to the intelligent equipment to realize optimal allocation of energy and help users save energy and reduce emissions.

2.1. Home energy management system architecture

Traditional energy management is simple and unidirectional, only through the metering meter on the total electricity consumption statistics, cannot collect and intelligent control of each electrical equipment power consumption data. Relying only on users to consciously turn off additional loads to achieve energy savings, the function is single and inefficient. The home energy management system is built based on communication technology and realizes the two-way flow of electricity and information by interconnecting power generation, energy storage, electricity consumption and external environment to realize real-time monitoring, intelligent processing and intelligent regulation. The architecture diagram of its system is shown in Figure 1. An ideal home energy management system mainly consists of distributed energy, advanced measurement system, intelligent control terminal and intelligent home appliances.

Home energy management systems are supplied by the grid, renewable energy generation, energy storage devices and electric vehicles. The grid is the main source of electricity supply, but the use of fossil fuels has an environmental impact. Renewable energy generation provides a new source of electricity through photovoltaics and wind power and can sell excess power to the grid. Energy storage devices improve the utilization of renewable energy generation by storing excess electricity through batteries. Electric vehicles can be used as loads when in use and as energy storage devices when idle, but charging behavior needs to be rationally guided to reduce the impact on the grid.

The Advanced Measurement Instrumentation System (AMI) is the core component of the home energy management system, which consists of a combination of technologies such as smart meters, home local area networks, measurement

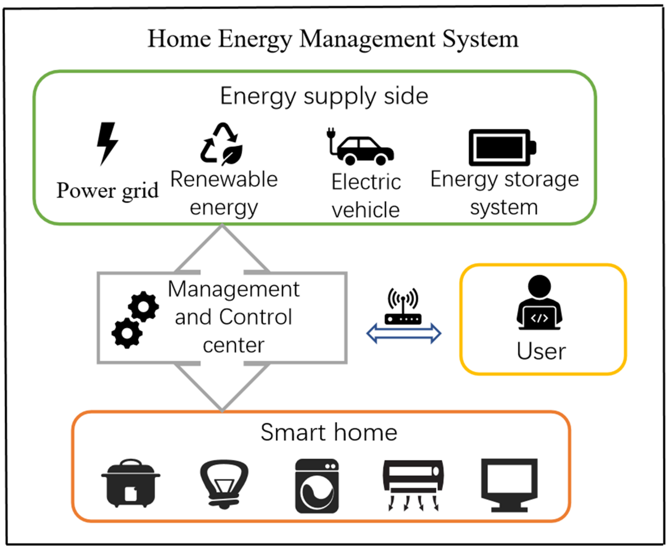

Figure 1: Home energy management system architecture

data management systems, and two-way communication networks. Smart meter is the most core device in AMI, with functions such as power monitoring, data storage, and two-way communication. The home local area network connects the smart meter, power consumption equipment, control center and other links, so that the whole home energy system becomes a whole. The measurement data management system can automatically collect the data monitored by the smart meters and analyze and process them. Two-way communication network realizes real-time exchange of information between power grid and users, data center and smart meters.

Intelligent control terminal is an indispensable part of the home energy management system, which optimizes the electricity load by analyzing and processing the electricity consumption data and environmental information obtained from sensors, smart sockets, and other components to realize the intelligence of home electricity consumption. At the same time, the intelligent control terminal can remotely start and shut down household appliances and carry out reasonable operation planning to reduce residential energy consumption.

Smart home appliances realize sensitive sensing, automatic adjustment, interactive intelligent control and energy saving through advanced technologies such as computer technology, Internet of Things technology and communication technology. As part of the smart home, smart appliances transform traditional home environments into residences with automation and intelligence to achieve user-friendly load control and create a comfortable, convenient, intelligent and safe living environment. Compared with the traditional home, the smart home changes the user's power structure and realizes the safe access to distributed power as well as the two-way flow of energy and information. The comparison between traditional home and smart home is shown in Table 1.

Table 1: Comparison of traditional home and smart home

Household form	Power supply	Direction of power transmission	Communications direction
Traditional home furnishing	Single supply of electricity from the grid	uni-directional	One-way/no communication
Smart home	Grid, photovoltaic, energy storage devices	bi-directionality	bi-directionality

2.2. Classification and modeling of household electricity loads

Electricity loads are an integral part of a residence. Users want to run loads during times when electricity prices are lower. Based on the time elasticity of electricity consumption of devices and the degree of user autonomy in response, household electricity loads can be categorized into rigid and flexible devices. In this paper, controllable electricity loads are optimally scheduled in terms of days. To minimize errors, a day is divided into 120 time periods, with each 1 hour divided into 5 equal time periods. Assume that the shortest operating time for any appliance load is 12 minutes, and anything over 12 minutes is calculated as a multiple of 12, with the power of the electrical equipment remaining constant for each period.

2.2.1. Rigid loads

Rigid loads are those that have fixed running times, are not flexible and controllable, and scheduling these loads will affect user demand. Therefore, such loads are not used as the optimization target for optimal scheduling of equipment energy consumption. Its mathematical model is shown in equation 1:

$$W_s = P_s \times T_s\,, \tag{1}$$

where W_s is the total energy consumption of the rigid load, P_s is the power rating of the rigid load, and T_s is the total operating hours of the rigid load.

2.2.2. Flexible loads

Flexible loads are controlled in a flexible way and can be actively involved in the optimization of household electricity consumption by planning load times according to the tariff or the wishes of the user. It has little impact on the user. Flexible loads can be divided into non-interruptible and interruptible loads. Non-interruptible loads cannot be interrupted and must run until the task is completed. Interruptible loads can be switched on and off at will during a set period, working intermittently to balance the demand for electricity.

(1) Interruptible load

Interruptible loads, as shown in Figure 2, can delay or interrupt operations, i.e., their power consumption intervals can be segmented and discontinuous, and they can be temporarily interrupted in the operating state to realize the scheduling strategy if the workload is guaranteed.

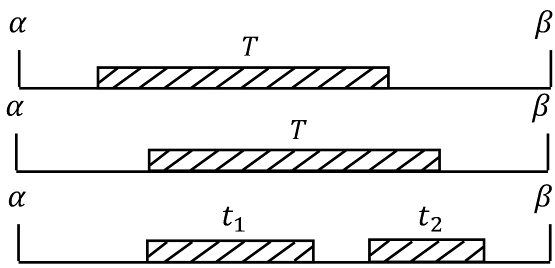

Figure 2: Schematic of interruptible load power usage

Interruptible loads are modeled as follows:

$$1 \leqslant \alpha_i \leqslant \beta_i \leqslant 120, \tag{2}$$

$$t_s \geqslant \alpha_i\,, \tag{3}$$

$$t_e \leqslant \beta_i\,, \tag{4}$$

$$\beta_i - \alpha_i \geqslant T_i\,, \tag{5}$$

$$x_i^k = \{0,1\}\,, \quad k \in [\alpha_i, \beta_i]\,, \tag{6}$$

$$x_i^k = 0, \quad k \notin [\alpha_i, \beta_i]\,, \tag{7}$$

$$\sum_{k=\alpha_i}^{\beta_i} x_i^k = T_i\,, \tag{8}$$

$$\sum_{l=1}^{n} t_l = T_i\,, \tag{9}$$

where i denotes the device number, t_s is the actual start time of the device, t_e is the actual shutdown time of the device, α_i is the earliest allowable start time of the device, β_i is the latest allowable shutdown time of the device, x_i^k denotes the operating state of the device in the k-th time period, and 1 denotes the running state, 0 indicates a stopped state, and the algebraic sum of the operating states of each time period within the time range in which the device is allowed to operate is equal to the operating time period T_i required for device i to complete the task, and is also equal to the sum of the operating times of each sub-segment t_l, and n is the number of sub-time periods in which the device operates.

(2) Uninterruptible load

Non-interruptible loads, as shown in Figure 3, can only be operated with delay, and once the power-using equipment has started operation, it will run continuously until the power-using task is completed.

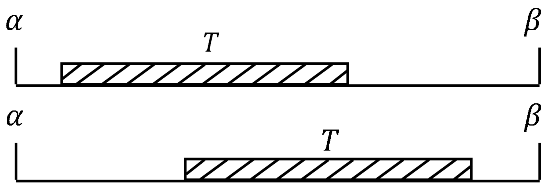

Figure 3: Schematic of uninterruptible load power usage

Uninterruptible loads are modeled as follows:

$$1 \leqslant \alpha_i \leqslant \beta_i \leqslant 120, \tag{10}$$

$$t_s \geqslant \alpha_i\,, \tag{11}$$

$$t_e \leqslant \beta_i\,, \tag{12}$$

$$\beta_i - \alpha_i \geqslant T_i\,, \tag{13}$$

$$x_i^k = 1, \quad k \in [t_s, t_e]\,, \tag{14}$$

$$x_i^k = 0, \quad k \notin [t_s, t_e]\,, \tag{15}$$

$$t_e - t_s + 1 = T_i\,, \tag{16}$$

where i denotes the device number, t_s is the actual start time of the device, t_e is the actual shutdown time of the device, α_i is the earliest start time allowed for the device, β_i is the latest shutdown time allowed for the device, x_i^k denotes the operating state of the device in the first time slot, 1 denotes the running state, 0 denotes the stopped state, and T_i is the operating duration of the device.

3. Analysis of electricity usage habits by proposed SK-mean clustering algorithm

Users need to determine the demand information of each participating scheduling device, including power, usage period and usage duration. Different users have different power usage habits and preferences, and if the optimization scheme does not meet their needs, they will refuse to participate in the response.

Therefore, it is important to provide relevant power consumption optimization strategies to improve customer satisfaction, and accurate power consumption behavior analysis can provide a reliable basis.

In order to reduce the discomfort of user participation in the optimal scheduling of equipment, this section proposes an improved K-mean clustering algorithm for the clustering analysis of user's power usage habits and introduces distribution metrics to define the scheduling type of each appliance. Finally, the scheduling parameters of the appliance are obtained, including the analysis of usage habits, scheduling time range, optimal start-up time, optimal shutdown time, scheduling type, load working hours and daily usage frequency. The results of these analyses are used as constraints for the scheduling model to derive a reasonable power usage optimization scheme.

3.1. Analysis of electricity consumption habits

3.1.1. Use of habit-fitting analysis

In this section, a circular coordinate fitting method is proposed to represent the 120 time periods divided into one day in coordinates, each time period corresponds to a two-dimensional coordinate (x, y), in which the coordinate $(0, 0)$ represents the 1st time period, the other coordinates are arranged in counter-clockwise order, and the Euclidean distances between two neighboring coordinate points are all 1. Taking into consideration the continuity of the time, the 1st period and the 120th time period will be connected, and all the coordinate points will be fitted into a circle as shown in Figure 4.

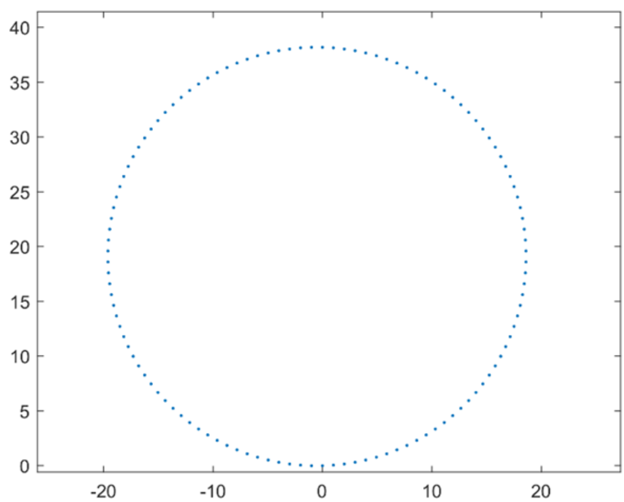

Figure 4: Schematic of coordinate fitting

After the circular coordinates were fitted, the equipment operation was analyzed to count the time interval and load of each run. The frequency of operation was converted into data points recorded in circular coordinates. The preprocessed data was used to determine the most appropriate number of clusters according to the elbow rule, with each cluster representing an appliance usage habit. The elbow rule uses the sum of squared errors (SSE) as the core metric, and when the number of clusters is smaller than the actual number of clusters, the SSE decreases more as the number of clusters increases and the degree of cluster aggregation increases. When the number of clusters reaches a critical point, the degree of distortion of the clusters is improved and the decrease in SSE decreases. This critical point is the true number of clusters of the data.

SSE is calculated as follows:

$$SSE = \sum_{i=1}^{k} \sum_{p \in C_i} |p - m_i|^2 , \tag{17}$$

where k is the number of clusters; C_i is the i-th cluster, p is the sample point in C_i, and m_i is the center of mass of C_i.

3.1.2. Scheduling time frames

First, the scheduling time range restricts the user's usage time, and the device cannot exceed this interval. Second, the improved K-mean clustering algorithm is used to cluster and analyze the data points in each period, divide them into sets of data points with similar characteristics, and derive the time interval of the user's habitual use of electricity as a constraint for each set. The more objects in the class, the more frequently the appliances are used in that time interval, and the users are accustomed to using the devices in that time interval. Finally, the sorted habits are prioritized, and weights are set to participate in the subsequent power optimization strategies to measure the user's power satisfaction. The detailed steps are presented in Section 4.

3.1.3. Optimal start/stop times

The optimal start-stop time is the time at which the user is most satisfied with the turn-on and turn-off times of the device. By counting the frequency distribution of turn-on and turn-off times when the user is using the device, the point in time with the highest frequency for each power usage habit is determined as the optimal start-stop time. During equipment scheduling, work schedules are generated as close as possible to the optimal start/stop time to minimize discomfort to users.

3.1.4. Types of equipment scheduling

Equipment scheduling types are categorized into interruptible and non-interruptible loads. Uninterruptible loads work for a fixed duration, and interruptible loads work for an irregular and highly variable duration. This paper introduces the distribution index and uses the coefficient of variation to calculate the dispersion degree of the continuous working time of the equipment to determine whether the equipment is interruptible or not.

The coefficient of variation was calculated as follows:

$$C.V = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}}{\overline{X}}, \tag{18}$$

where X_i is the working hours of the i-th run of the device, $\overline{X}$ are the average working hours, and n is the total number of runs of the device.

Power usage data is analyzed to obtain the number of times the equipment is used per day. For non-interruptible loads, the number of times per day usage indicates the number of tasks per day of the equipment if each work duration is the average daily run duration. For interruptible loads, it represents the number of subtasks that can be divided by completing the maximum number of average daily operating hours.

Defined in the following equation:

$$N_i = round\left(\frac{T_1}{T_2}\right), \tag{19}$$

where T_1 is the average daily runtime of the device, T_2 is the average per runtime of the device, N_i is the number of daily uses of device i, and *round* is a rounding operation.

3.2. Proposed SK-means clustering algorithm

3.2.1. Traditional K-means algorithm

Clustering is a common data analysis method that categorizes objects in a dataset by finding similar structures. The K-mean clustering algorithm is one of the most widely used clustering algorithms which is simple, fast and suitable for large scale datasets. The algorithm uses Euclidean distance as a similarity metric and solves for the sum of the minimum distances of the samples from the clustering centers through multiple iterations as a way to classify data with similar features in the same set.

The K-mean clustering algorithm is simple and convenient, but suffers from poor global optimization seeking ability, isolated point influence and initial center sensitivity. To improve accuracy, this paper improves the K-mean clustering algorithm.

3.2.2. Proposed SK-means algorithm

In this paper, SK-means algorithm is proposed to improve for the shortcomings of K-means clustering algorithm. The improvement scheme includes changing the method of finding the value of the clustering center in the new round, introducing the strategy of accelerated transfer of the clustering center and the parameter-control strategy of parabolic incremental type function, and the adaptive control of the sample range. Small-scale screening of dissimilar samples in the early stage speeds up convergence; large-scale global exploration in the late stage avoids local optimization.

Given the weight value u, the curve increment function is equation 20, and u increases with the number of iterations, with slow growth in the early stage and faster growth in the later stage. In the process of updating the clustering center in each iteration, the range of sample points for calculating the new clustering center is controlled. The average distance between all samples in the cluster and the cluster clustering center of the cluster is calculated by equation 21, and then the average of a subset of the part of the distance from the clustering center that is less than $u \times L_{\text{ave}}$ is selected as the new round of clustering center. After iterative updating, the algorithm will find the optimal classification faster.

$$u = (u_{\min} - u_{\max}) \times \left(1 - \left(\frac{d}{D}\right)^{\delta}\right)^{1/\delta} + u_{\max}\,, \tag{20}$$

where $u_{\max}$, $u_{\min}$ are the maximum and minimum values of the preset u, d is the current number of iterations, D is the total number of iterations, and δ controls the curve concave amplitude.

$$L_{\text{ave}} = \frac{\sum\limits_{x_i \in V_j} d\left(x_i, \mu_j\right)}{s_j}\,, \tag{21}$$

where x_i denotes the i-th sample point, V_j denotes the set of sample points of the j-th class, μ_j denotes the clustering center of the j-th class, and s_j denotes the total number of samples of the j-th class.

This strategy for clustering large-scale multi-category data greatly compresses the distance calculation, reduces the average elapsed time, and mitigates the influence of boundary points and isolated points on the clustering results, effectively improving the clustering accuracy.

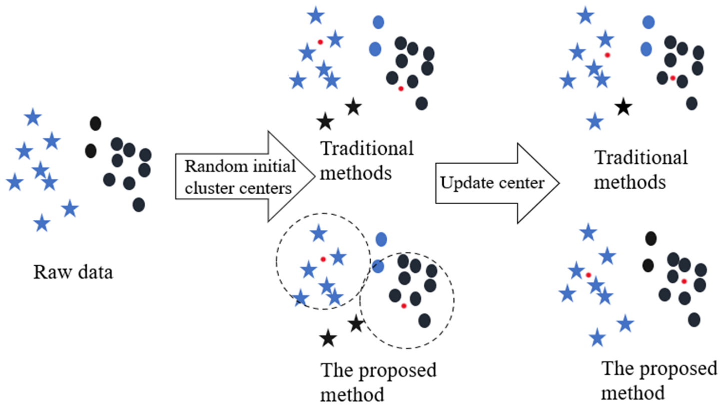

Figure 5: Schematic of iteration

The SK-means algorithm is calculated as follows:

Step 1: First randomly select k samples as the center of the initial clustering;

Step 2: Calculate the distance between each sample and each clustering center, and divide the clusters according to the minimum distance criterion;

Step 3: The average distance L_{ave} and range weight u of all samples in the cluster from the cluster's clustering center are calculated using equations (20) and (21), respectively.

Step 4: Select the samples in the cluster whose distance from the clustering center is less than $u \times L_{\text{ave}}$, calculate the average of these points as the clustering center for the next round of clustering, and update the set of clustering centers.

Step 5: Cycle steps 2 through 4 until the division of all samples no longer changes.

3.2.3. Performance of SK-means algorithm

To accurately analyze the clustering performance of SK-means clustering algorithm, this paper's algorithm is compared with traditional K-means algorithm and PSO-K-means algorithm. Let the population size of several algorithms N=50, the number of iterations 100, and the parabolic increasing type function in $\delta = 1.6$, $u_{\max} = 1.1$, $u_{\min} = 0.7$.

The experiments are tested using Iris, Glass, Wine, and Balance-scale from the UCI machine learning database. Among them, Iris is a dataset for recognizing different helianthus plants; Glass is a glass recognition dataset, which belongs to multi-category dataset; Wine is a dataset for recognizing liquor, which belongs to high-dimensional dataset; Balance-scale is a dataset for simulating the results of psychological experiments, which belongs to multi-sample dataset. In this paper, F-*measure* is used as the external evaluation index of clustering results, and the size of F- *measure* value is between 0 and 1, and the larger its value is, the better the clustering effect is. The detailed information of each dataset is shown in Table 2.

Table 2: Details of the data set

Data set	Sample size	Attribute dimension	Total number of categories	Category distribution
Iris	150	4	3	50, 50, 50
Glass	214	9	6	70, 76, 17, 13, 9, 29
Wine	178	13	3	59, 71, 48
Balance-scale	625	4	3	49, 288, 288

From Tables 3–6, it can be seen that the traditional K-means algorithm has poor global optimization ability, and it is easy to fall into local optimal solutions. The PSO-K-means algorithm improves the optimization ability, but there is still the problem of premature maturity. Compared with traditional K-means and PSO-K-means, the algorithm proposed in this paper can avoid local optimal solutions and significantly improve the clustering effect. The accuracy is higher in terms of the optimal value and the average value. In the tests on Iris, Glass and Wine datasets, the optimal clustering results are obtained in each run. Therefore, the SK-means clustering algorithm proposed in this paper is suitable for clustering analysis of real power datasets.

Table 3: Performance comparison on dataset Iris

Data set	*F-measure*	K-means	PSO-K-means	SK-means
Iris	Best	0.8918	0.9329	**0.9466**
	Worst	0.8918	0.8853	**0.9200**
	Mean	0.8918	0.9099	**0.9293**

Table 4: Performance comparison on dataset Glass

Data set	*F-measure*	K-means	PSO-K-means	SK-means
Glass	Best	0.4322	0.4903	**0.4997**
	Worst	0.3839	0.4117	**0.4950**
	Mean	0.3926	0.4312	**0.4966**

Table 5: Performance comparison on dataset Wine

Data set	*F-measure*	K-means	PSO-K-means	SK-means
Wine	Best	0.7032	0.7199	**0.7315**
	Worst	0.7032	0.7082	**0.7093**
	Mean	0.7032	0.7120	**0.7205**

Table 6: Comparison of performance on dataset Balance-scale

Data set	*F-measure*	K-means	PSO-K-means	SK-means
Balance-scale	Best	0.4684	0.4836	**0.5383**
	Worst	0.4455	**0.4582**	0.4556
	Mean	0.4559	0.4683	**0.4712**

3.3. Analysis of user habit examples

3.3.1. Data source

The data used in this paper for the arithmetic analysis is taken from the publicly available UK-DALE dataset from the UK Energy Data Center (UKERC) [30]. Electricity data is selected for evaluation for Household 1, which has 4 members, 2 adults and 2 children. The dataset recorded the power consumed by the devices in the house and the electricity demand of the whole household every 6 seconds for a total of 786 days.

In this algorithm, several types of appliances commonly used in the household1 are selected for analysis, and a total of seven controllable appliances, including water pump, washing machine, dishwasher, electric kettle, oven, microwave oven, and vacuum cleaner, are selected for the analysis of electricity consumption behavior, and the dataset information of each appliance is shown in Table 7.

Table 7: Data set information for each appliance

Installations	Durations
Dehumidifiers	2014.1.1–2015.1.1
Fridge	2014.1.1–2015.1.1
Electric kettle	2014.1.1–2015.1.1
Ovens	2014.1.1–2015.1.1
Microwaves	2014.1.1–2015.1.1
Water storage	2014.1.1–2015.1.1
Dust catcher	2013.2.15–2014.12.24

3.3.2. Analysis results

This section analyzes the power usage habits of washing machines and vacuum cleaners. The washing machine is a non-interruptible device with three power usage habits, and the vacuum cleaner is an interruptible device with four power usage habits. The other devices are analyzed in the same way and steps as the two devices above, and the final results are presented in tabular form.

The operation of the washing machine and vacuum cleaner were first analyzed, and the period and load of each operation within the monitoring time range were counted one by one, and the final result of the load curve of the washing machine is shown in Figure 6.

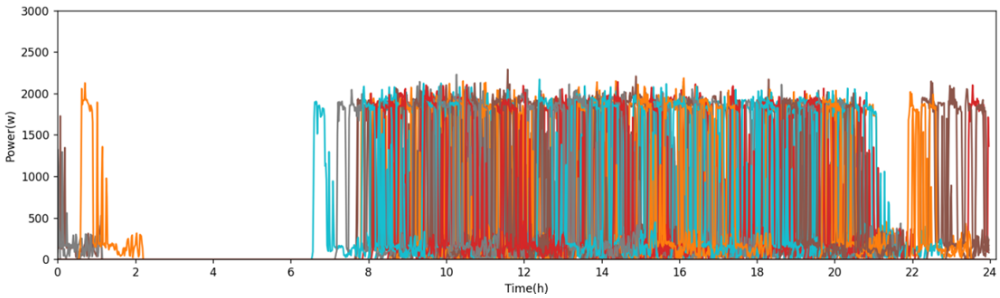

Figure 6: Washing machine load profile

Similarly, the results of the load curve for the vacuum cleaner are shown in Figure 7.

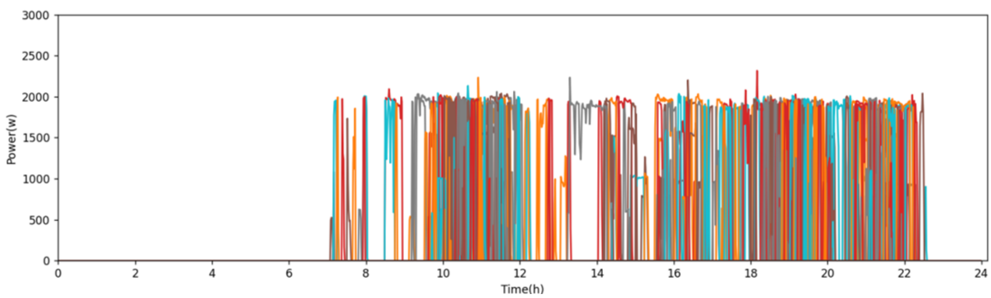

Figure 7: Vacuum cleaner load profile

The operation in the above figure will be run for 120 periods of running frequency statistics, for example, if the equipment is running from 09:00 to 10:00, then the frequency of the 46th period to the 50th period in the running frequency statistics will be recorded as 1. After adding up all the running statistics, the washing machine's 120 periods of each period of running frequency statistics are shown in Figure 8.

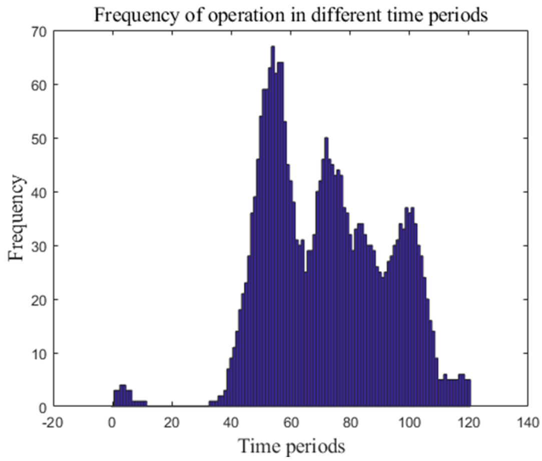

Figure 8: Running frequency statistics

Next, by circular coordinate fitting, the time periods from 0 to 120 are represented one by one corresponding to a two-dimensional coordinate (x, y), where $(0, 0)$ denotes the first period, and the rest are arranged in counterclockwise order. The frequency of each period is reflected by the density of the data points, for example, if the washing machine has been run 3 times in the first period, the frequency is 3, and there will be 3 data points on the corresponding coordinates $(0, 0)$. The running frequency statistics of all 120 time periods are fitted to the circular coordinate data point statistics, and the results are shown in Figure 9, where the axes indicate the number of data points.

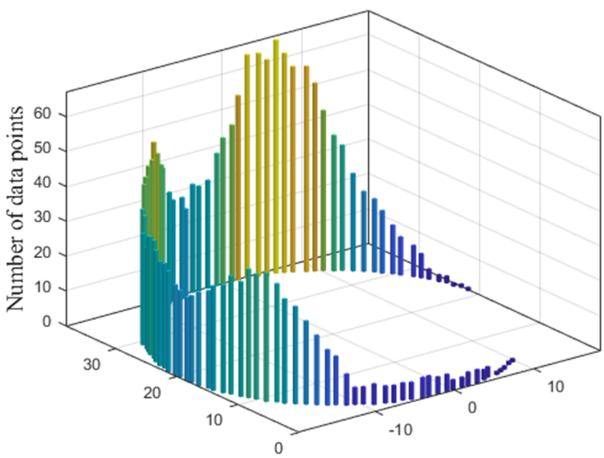

Figure 9: Circular coordinate data point statistics

Similarly, the frequency of operation statistics and the circular coordinate data point statistics of the vacuum cleaner are shown in Figure 10 and Figure 11.

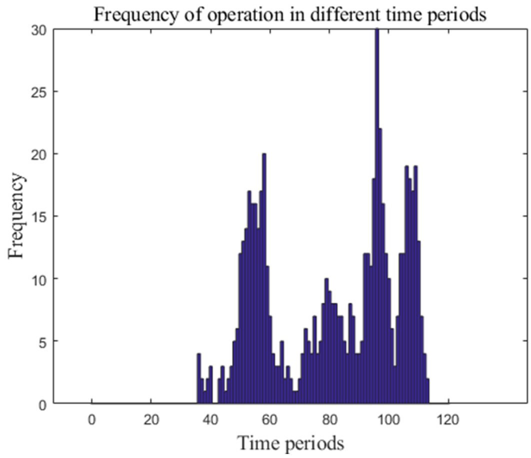

Figure 10: Running frequency statistics

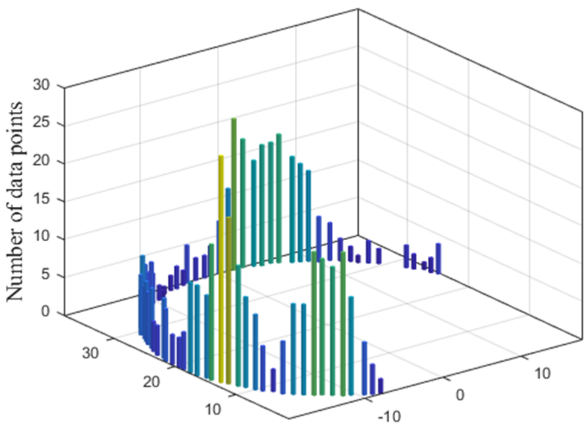

Figure 11: Circular coordinate data point statistics

(1) Analysis of usage habits

After the data were preprocessed, the fitted data were subjected to the elbow rule operation, and the results are shown in Fig. 12, where the degree of distortion of the clusters was greatly improved and the decrease of SSE plummeted at $k = 3$. Therefore, the optimal number of clusters k is taken as 3, which means that there are 3 intervals of washing machine usage habits in this family. Similarly, as shown in Figure 13, there are 4 usage habit intervals for vacuum cleaners in this household.

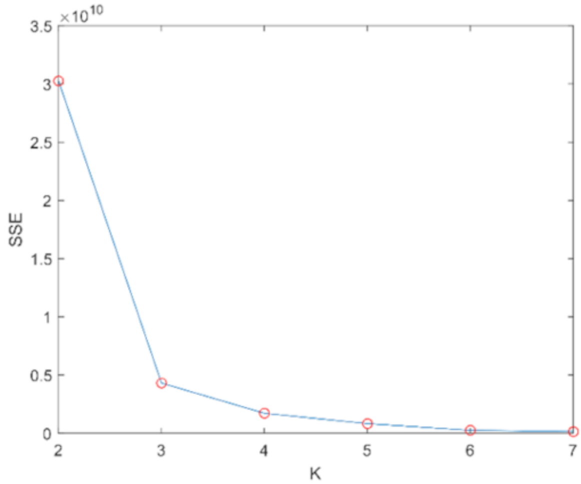

Figure 12: SSE ($k = 3$)

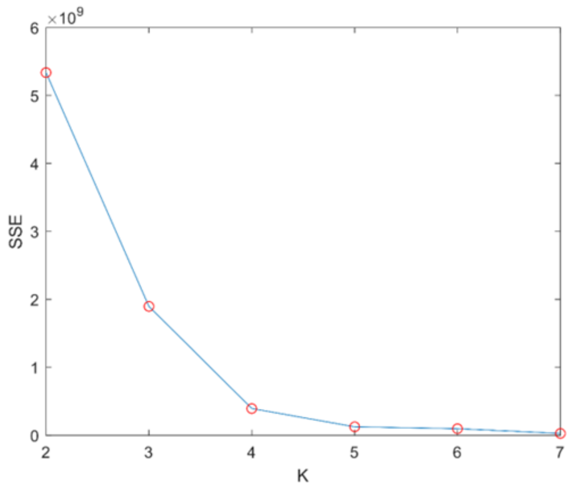

Figure 13: SSE ($k = 4$)

(2) Scheduling time range

According to the number k of washing machine habit intervals obtained, the SK-means algorithm is used to perform cluster analysis on the fitted data points for each time period, and the results of the clustering are shown in Fig. 14, which divides the user's habits into three classes and prioritizes the habits according to the density of the classes from high to low: the first power habit interval [33, 65], i.e., from 06:24 to 13:00. The second interval [66, 88], i.e. from 13:00 to 17:36, and the third interval [1, 11], [89, 120], i.e. from 17:36 to 02:12.

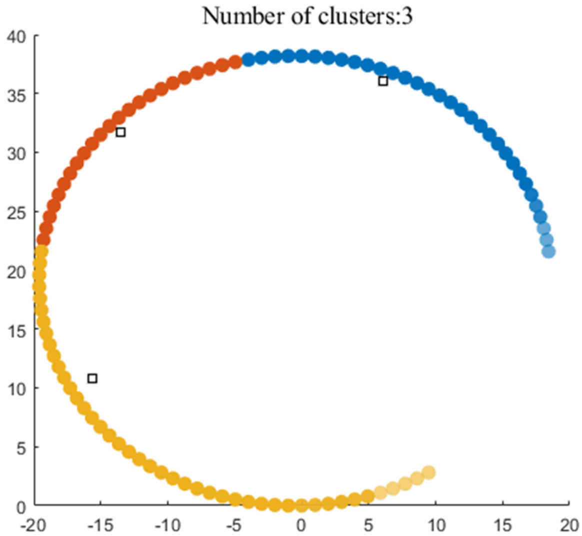

Figure 14: Clustering results (3 clusters)

Similarly, the results of vacuum cleaner clustering are shown in Figure 15, which divides the user's habits into four classes and prioritizes the habits, based on the density in the class from high to low: the first power habit interval [36, 40], [43, 66], i.e., 07:00 to 08:00, 08:24 to 13:12. The second power habit interval [88, 101], i.e., 17:24 to 20:12. The third power habit interval [102, 113], i.e., 20:12

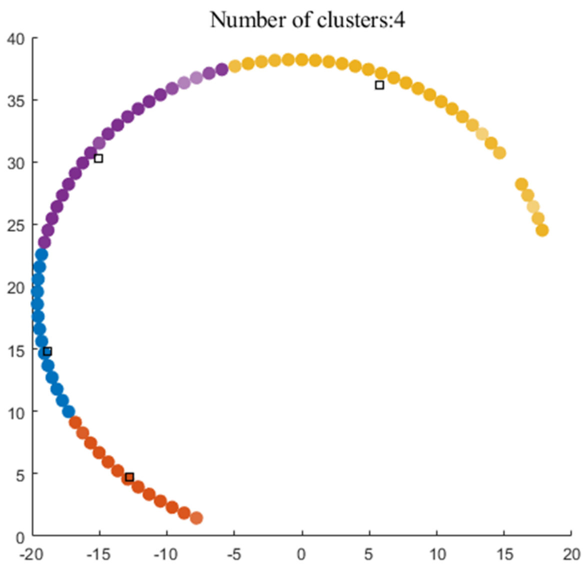

Figure 15: Clustering results (4 clusters)

to 22:36. The fourth power habit interval [67, 87], i.e., 20:12 to 22:36. The third power habit interval [102, 113], i.e., 17:24 to 20:12. The third interval [102, 113] is from 20:12 to 22:36. The fourth interval [67, 87] is from 13:12 to 17:24.

(3) Optimal start and stop time

The statistics of the equipment turn-on time and turn-off time, from the data set of the family in a year of the distribution of the time nodes of the washing machine on and off, will correspond to the division of the 120 time periods, the statistical results are shown in Figure 16 and Figure 17. It can be seen that the

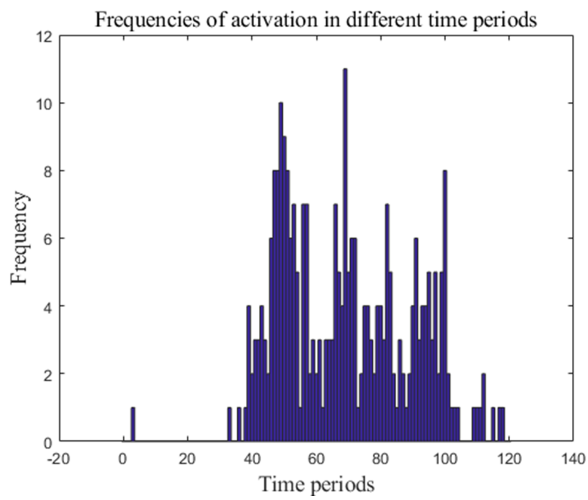

Figure 16: Frequency of activation (washing machine)

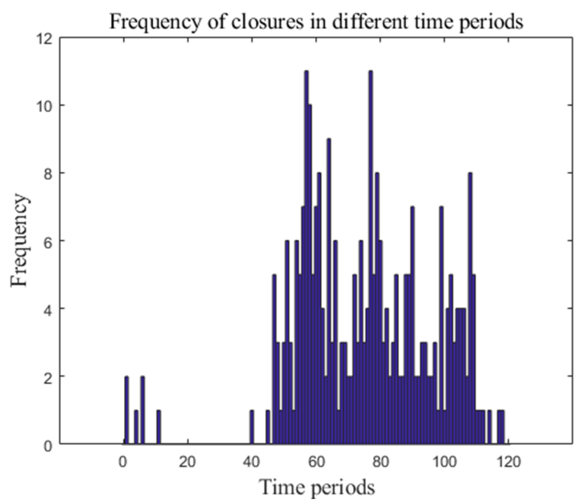

Figure 17: Frequency of closures (washing machine)

frequency of turning on the washing machine is highest in the 49th time slot, i.e., 09:36 to 09:48, and often turns off the washing machine in the 57th time slot, i.e., 11:12 to 11:24, under the first electricity habit of this household user. This can be set as the optimal start/stop time for the washing machine under this habit. The optimal start/stop times for the second habit are 69th and 77th hours. For the third power habit, the optimal start/stop times are 100th and 108th.

Similarly, the statistics of vacuum cleaner equipment on time and off time are shown in Figure 18 and Figure 19. The frequency of turning on the vacuum

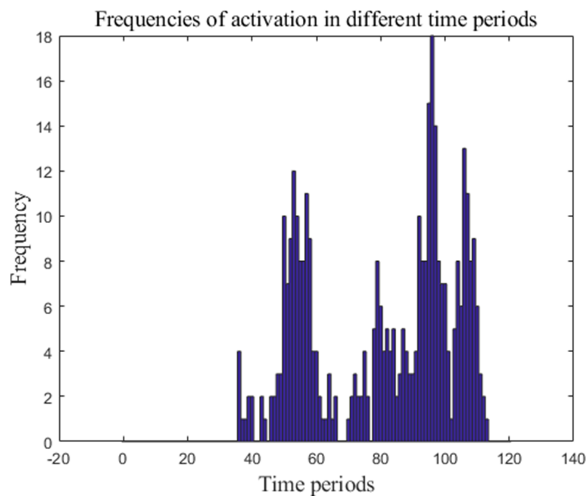

Figure 18: Frequency of activation (vacuum cleaner)

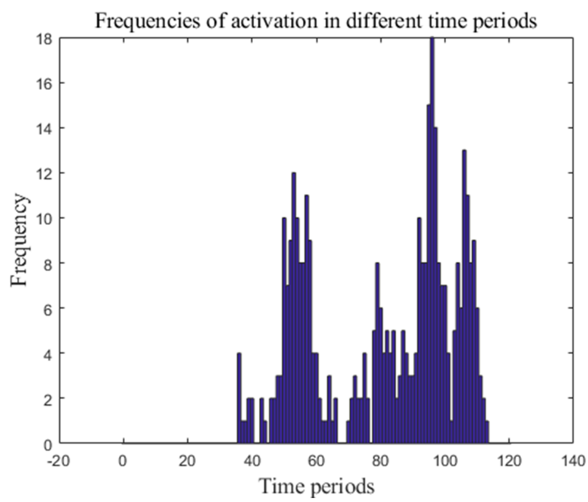

Figure 19: Frequency of closures (vacuum cleaner)

cleaner under the first electricity habit of this household user is highest in the 53rd hour, i.e., the interval from 10:24 to 10:36, and often turns off the vacuum cleaner in the 58th hour, i.e., the interval from 11:24 to 11:36. This can be set as the optimal start/stop time of the vacuum cleaner for this habit. The best start/stop times for the second power habit are at 96th and 102nd hour. The best start/stop time for the third power habit is in the 106th and 109th hours. For the fourth power habit, the optimal start/stop times are 79th and 84th.

(4) Scheduling type of equipment

The continuous running hours of each time the washing machine is turned on in a year in this household are counted, and the results are shown in Figure 20. And analyze the distribution index of the equipment, the average daily running hours, the average single running hours, the number of daily use and the type of scheduling, and the results are shown in Table 8. Where, $C.V = 0.1893$, the coefficient of variation is small, indicating that the working hours of users are

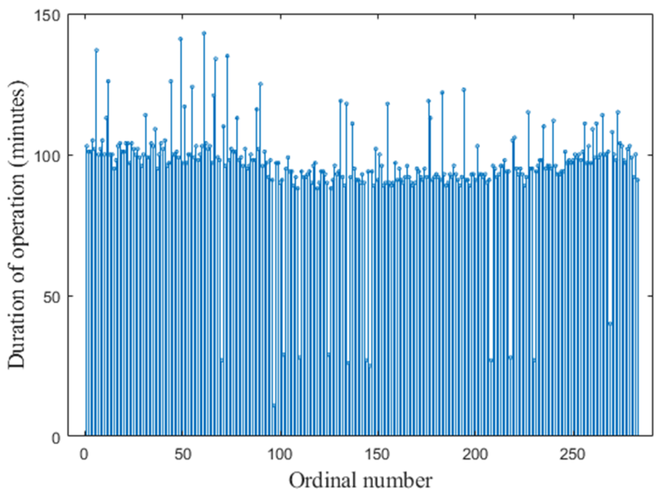

Figure 20: Statistics of washing machine running hours

Table 8: Habit information

Parameter category	Digital
Average length of each run	96 minutes
Average daily operating hours	105 minutes
Number of uses per day	1
Coefficient of variation ($C.V$)	0.1893
Type of dispatch	Uninterruptible load

basically fixed each time they use this equipment, so it is defined as a non-interruptible load. The washing machine is used once a day, and the duration of each use is 96 minutes.

Similarly, the sustained run length of the vacuum cleaner per turn-on is shown in Figure 21. The results of analyzing the distribution metrics of the device, the average daily runtime, the average single runtime, the number of daily uses, and the scheduling type are shown in Table 9. Where, $C.V = 0.8933$, the coefficient of variation is large, indicating that the users do not work for a fixed number of hours each time they use this equipment, so it is defined as an interruptible load. On average, the vacuum cleaner was used three times per day for a total of 42 minutes.

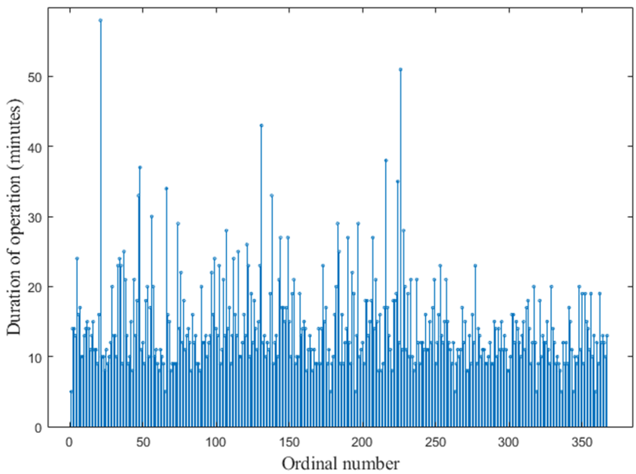

Figure 21: Vacuum cleaner running hours statistics

Table 9: Habit information

Parameter category	Digital
Average length of each run	15 minutes
Average daily operating hours	42 minutes
Number of uses per day	3
Coefficient of variation ($C.V$)	0.8933
Type of dispatch	Interruptible load

The rest of the devices were analyzed by the same method, and the data on user habits for all the devices are shown in Table 10.

Table 10: Data of user habits

Parameter category	Washing machine	Vacuum cleaner	Water pump	Electric kettle	Oven	Microwave oven
First range	[33, 65]	[36, 40] [43, 66]	[39, 64]	[29, 53]	[31, 56]	[33, 54]
First optimal start stop time	start 49, stop 57	start 53, stop 58	start 47, stop 60	start 38, stop 38	start 40, stop 40	start 40, stop 40
Second range	[66, 88]	[88, 101]	[65, 83]	[54, 78]	[57, 70]	[55, 74]
Second optimal start stop time	start 69, stop 77	start 96, stop 102	start 68, stop 81	start 62, stop 62	start 64, stop 64	start 63, stop 63
Third range	[1, 11] [89, 120]	[102, 113]	[84, 120] [1, 5]	[79, 119]	[73, 95]	[80, 120] [1, 5]
Third optimal start stop time	start 100, stop 108	start 106, stop 109	start 94, stop 96	start, 89 stop 89	start 91, stop 92	start 93, stop 93
Fourth range	–	[67, 87]	–	–	[96, 120]	–
Fourth optimal start stop time	–	start 79, stop 84	–	–	start 99, stop 99	–
Average running time (each time)	96 min	15 min	77 min	5 min	8 min	9 min
Average running time (daily)	105 min	42 min	318 min	15 min	25 min	30 min
Daily usage times	1	3	4	3	3	3
C.V	0.1893	0.8933	1.7929	0.2113	0.2279	0.2162
Scheduling type	Non interruptible	Interruptible	Interruptible	Non interruptible	Non interruptible	Non interruptible

4. Home smart power optimization model and algorithm

Suitable optimization strategies for household electricity consumption can both save costs and stabilize grid fluctuations. In this section, a multi-objective optimization model is developed based on the analysis of user habits to adjust electricity demand and obtain economic benefits by considering economy, comfort and peak-to-average ratio. Household electricity optimization is a nonlinear 0-1 planning problem containing multiple constraints, which requires a reduction in electricity expenditure, an increase in user satisfaction and a reduction in the peak-to-average ratio. Optimization algorithms have inherent drawbacks and cannot achieve optimal planning. Therefore, in this paper, an improved artificial bee colony algorithm is invoked to solve the household electricity optimization problem and achieve more efficient electricity planning.

4.1. Multi-objective function optimization model

4.1.1. Electricity costs

For users, the main purpose of their participation in optimal scheduling is to minimize power expenditure without affecting the demand for power, so the cost of power consumption is used as a major objective of optimal control of power consumption.

In this paper, one hour is divided equally into five equal time periods, and a total of 120 time periods are set. Therefore, the expression of the objective function of the electricity cost of household equipment in a day is:

$$C = \sum_{k=1}^{120} \sum_{i=1}^{n} x_i^k \times ep_k \times \frac{P}{5}, \tag{22}$$

where x_i^k is the operating state of device i in time period k, which takes the value of 1 when it is running and 0 when it is not running, ep_k is the tariff for the k-th time period, P is the rated power of the device, and n is the number of devices involved in scheduling.

4.1.2. Satisfaction with electricity consumption

Customer satisfaction, or comfort with electricity, refers to the impact of changes in the electricity schedule on the customer experience. Shifting the customer load reduces customer experience, even though the customer sets the working period of each electricity device but wants to complete the electricity consumption task within the customary time. User satisfaction is related to the degree of matching of load scheduling strategy, the more the scheduling strategy conforms to the user's habits, the higher the user satisfaction.

This paper proposes different measures of satisfaction based on the electricity consumption characteristics of the two types of controllable electricity loads.

(1) Uninterruptible load

The previous section has already derived the interval of each power usage habit through cluster analysis and prioritized the power usage habits, so the habit dependence coefficient γ is introduced here to indicate the degree of user's dependence on each power usage habit, and the larger the proportion of data points of each power usage habit, the higher the value of γ is, and the higher the satisfaction will be when the loads are dispatched to be used in this time interval, the expression is shown as follows.

$$\gamma_i = \frac{n_i}{N}, \tag{23}$$

where, γ_i denotes the dependency coefficient of the i-th power usage habit, N is the total number of data points involved in clustering, and n_i is the number of data points assigned to the i-th power usage habit.

Considering that uninterruptible loads run continuously until the power usage task is completed, this paper measures the satisfaction of uninterruptible loads in terms of the relative distance between the actual start time of the load and the optimal turn-on time under that power usage habit, both starting the task under the optimal turn-on time of the user will result in the highest level of user satisfaction.

Therefore, the satisfaction measure function of the uninterruptible load is defined as:

$$f_1 = \begin{cases} \dfrac{\beta^{\left|t_s - t^i_{sbest}\right|}}{\gamma_i} & t_s \neq t^i_{sbest}, \\[2ex] \dfrac{1}{\gamma_i} & t_s = t^i_{sbest}, \end{cases} \tag{24}$$

where t_s is the actual start time of the device and t^i_{sbest} is the optimal turn-on time for the i-th power usage habit, $\beta > 1$. So, the smaller the value of the satisfaction f_1 of the uninterruptible load, the higher the user comfort.

(2) Interruptible load

Because of the interruptible load's electricity consumption characteristics whose operating time can be interrupted, the satisfaction of interruptible load's usage should be measured by considering both the equipment's on time and off time in addition to the user's dependence on each electricity consumption habit.

Therefore, the satisfaction measure function of interruptible load is defined as:

$$f_2 = \begin{cases} \sum_{i=1}^{m} \frac{\beta^{\left|t_s - t_{sbest}^i\right| + \left|t_e - t_{ebest}^i\right|}}{\gamma_i} & t_s \neq t_{sbest}^i, \quad t_e \neq t_{ebest}^i\,, \\ \sum_{i=1}^{m} \frac{1}{\gamma_i} & t_s = t_{sbest}^i, \quad t_e = t_{ebest}^i\,, \end{cases} \tag{25}$$

where, m is the number of subtasks interrupted by the load, t_s is the actual start time of the device, t_e is the actual turn off time of the device, t_{sbest}^i is the optimal turn on time for the i-th power usage habit, t_{ebest}^i is the optimal turn off time for the i-th power usage habit, and $\beta > 1$. Therefore, the smaller the value of the interruptible load's satisfaction, f_2, the higher the user comfort.

The final user electricity satisfaction function F is the sum of the satisfaction values of the two types of loads, so the smaller the value of the final user's electricity satisfaction F, the higher the user's comfort is indicated, as shown in equation (26):

$$F = \sum_{p=1}^{a_1} f_1^p + \sum_{q=1}^{a_2} f_2^q\,, \tag{26}$$

where f_1^p is the satisfaction of the non-interruptible load p and a_1 is the total number of non-interruptible loads, f_2^q is the satisfaction of the interruptible load q and a_2 is the total number of interruptible loads.

4.1.3. Peak-to-average ratio

The peak-to-average ratio is the ratio of the peak load to the average of total power consumption in a power system. In household electricity consumption, the peak-to-average ratio reflects the fluctuation of electricity consumption during the day. It avoids users shifting a large amount of load from high tariff hours to low tariff hours, which results in inverting the peak and trough times of electricity consumption, increasing the peak-to-valley difference of the grid, and adversely affecting the operation of the grid. Reducing the peak-to-average ratio (PAR) is one of the optimization objectives in this paper, which helps to maintain the stability and reliability of the grid. The formula for its calculation is as follows:

$$PAR = \frac{Load_{\max}}{Load_{\text{mean}}}\,, \tag{27}$$

$$Load_{\text{mean}} = \frac{\sum_{i=1}^{24} Load_i}{24}\,, \tag{28}$$

where $Load_{\max}$ is the peak load of the household in a day and $Load_{\text{mean}}$ is the average of the total power consumption of the household in a day.

Obviously, the three factors conflict with each other, and one side is often sacrificed in the optimization process. In this paper, we provide an energy optimization scheme that 1. Reduces the electricity bill and adjusts the use of appliances to low tariff periods; 2. Ensures customer satisfaction without changing electricity usage habits; and 3. Minimizes the negative impact of scheduling on the grid.

In this paper, we use linear weighting to combine cost, satisfaction and peak-to-average ratio metrics to build a multi-objective optimization function with constraints and normalize the objectives.

Ultimately, the objective function expression is:

$$M = \omega_1 \frac{C - C_{\min}}{C_{\max} - C_{\min}} + \omega_2 \frac{F - F_{\min}}{F_{\max} - F_{\min}} + \omega_3 \frac{PAR - PAR_{\min}}{PAR_{\max} - PAR_{\min}}, \tag{29}$$

where, ω_1, ω_2, ω_3 are weighting factors and the sum is 1. By setting different weighting factors to determine the importance of different optimization objectives, it adapts to the electricity consumption habits and purposes of different families.

4.2. ABC-MND algorithm for optimal home appliance scheduling

Intelligent algorithms have been applied to household electricity planning in many applications due to the advantages of being able to solve complex problems and being easy to implement, etc. Currently, optimization algorithms are mainly focused on meta-heuristic algorithms [31] such as Genetic Algorithm (GA), Gray Wolf Algorithm (GWO), Particle Swarm Optimization Algorithm (PSO), and Artificial Bee Colony Algorithm (ABC). In this paper, an improved artificial bee colony algorithm (ABC-MND) is used to solve the objective function according to the characteristics of the household electricity optimization problem.

The artificial bee colony algorithm is an optimization algorithm proposed by Karaboga based on the cooperative behavior of bees in division of labor [32]. Several literatures have achieved significant results by improving this algorithm in solving robot path planning problems [33], image encryption domain [34], solving schedule problems [35], and multi-objective flexible job shop scheduling problems [36]. The artificial bee colony algorithm is a population intelligent optimization technique, and when applied to multi-objective function optimization problems, its advantages include strong robustness and parallelism, as well as good global search capability. In this paper, the improved artificial bee colony algorithm ABC-MND [37] is used, which has high convergence speed and strong optimization search ability, and can obtain the optimal solution in a short time, while reducing the computational cost. The specific steps of the algorithm are as follows:

(1) Initialization of bee colonies

The initial population is generated using the random initialization method as follows:

$$X_i^d = X_{\min}^d + rand\,(0,1) \times \left(X_{\max}^d - X_{\min}^d\right), \tag{30}$$

where $i = 1, 2, \ldots, SN$, SN is the population size, $d = 1, 2, \ldots, D$, $X_{\max}^d$ and $X_{\min}^d$ are the upper and lower bounds of the d-th dimension of the search space.

(2) Hired bee stage

Each employed bee will randomly select a location around the current location to search, search according to equation (31) to generate a new nectar source, if a better solution is found then greedy selection is used, the nectar source with high adaptation will replace the old one, update its own location and set the counter to 0. If a better nectar source is not found, then the counter is increased by 1.

$$x_i^{t+1} = x_i^t + \varphi \times \left(x_i^t - x_j\right), \tag{31}$$

where $i \neq j$, x_j represents a neighboring nectar source, a nectar source not equal to i is randomly selected from the total nectar sources, and φ is a random number taking values in $[-1, 1]$.

(3) Follow the bee stage

In ABC-MND algorithm, the follower bees will only harvest honey in the vicinity of the optimal nectar source, the concept of multivariate normal distribution is introduced to randomly generate nectar clusters conforming to the multivariate normal distribution in the vicinity of the optimal nectar source, and the closer the location to the optimal nectar source produces more nectar sources with higher density, and the generated nectar clusters $X_{mnd} = [x_1, x_2, \ldots, x_d]$ are satisfied:

$$X_{mnd} \sim N\,(\mu, \Sigma)\,, \tag{32}$$

$$\mu = E\,(X_{mnd}) = (\mu_1, \mu_2, \cdots, \mu_d)\,, \tag{33}$$

$$\Sigma_{i,j} = Cov\left(x_i, x_j\right), \tag{34}$$

μ is the mean value, and in this paper, we take μ to be the global optimal solution, $\mu = x_{best}$.

Σ is the covariance matrix, and in this paper, we take $\Sigma = \begin{bmatrix} 0.3 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0.3 \end{bmatrix}$.

As an example, in 3-dimensional space, the nectar cluster generated at (1, 1, 1) as the center of the nectar source conforms to a multivariate normal distribution as shown in Fig. 22.

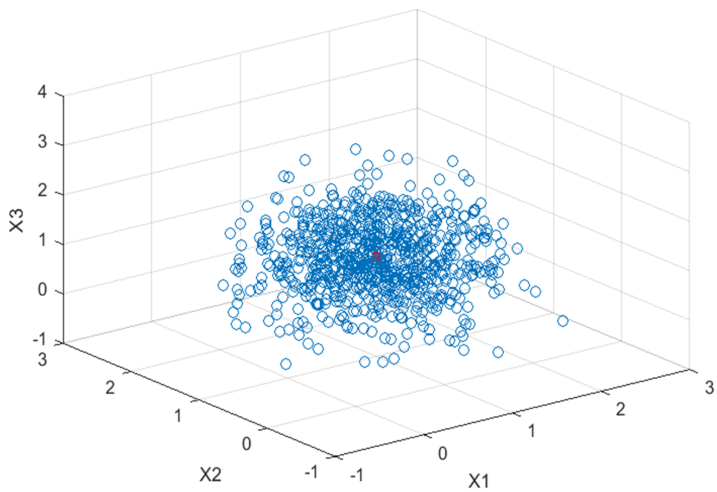

Figure 22: Three-dimensional nectar cluster

Then the following bees are commanded to harvest honey in the optimal nectar cluster X_{mnd}, and Eq. (35) is utilized after finding the target nectar source. This strategy allows the algorithm to retain the nature of elite guidance, which enhances local exploitation while maintaining colony diversity, prevents premature convergence, and finally follows greedy selection to retain the high-quality nectar source. If the following bee does not find a better nectar source in the optimal nectar colony, the counter of the optimal nectar source is increased by 1, and it enters the scouting bee phase when a predefined number of times is reached.

$$x_{mi}^{t+1} = x_{mi}^{t} + \varphi \times \left(x_{mi}^{t} - x_{mj}\right), \tag{35}$$

where $x_{mi},\ x_{mj} \in X_{mnd}$.

(4) Scout bee stage

The scout bee stage in the classical ABC algorithm will discard the nectar source that will not be updated many times, employing bees to become scout bees and randomly generating a new nectar source to replace it, this updating will lead to slower convergence of the algorithm, in the ABC-MND algorithm in order to allow the scout bees to exchange information with more than one good bee in the colony, the source is re-determined by using Eqs. (36), (37), which guides the generation of nectar source in a more optimal location, and introduces the perturbation coefficient α, which avoids getting stuck in a local optimum.

$$S = \frac{(x_1 + x_2 + \cdots + x_n)}{3}, \tag{36}$$

$$x_i = x_{rand} + \alpha \times (x_{rand} - \alpha \times S), \tag{37}$$

where $x_1, x_2 \ldots, x_n$ are the top n nectar sources optimally ranked by fitness, x_{rand} are the nectar sources randomly initialized using Eq. (30), and α is taken as a uniformly distributed random number in $[0, 2]$.

The specific flow of the ABC-MND algorithm is shown in Figure 23.

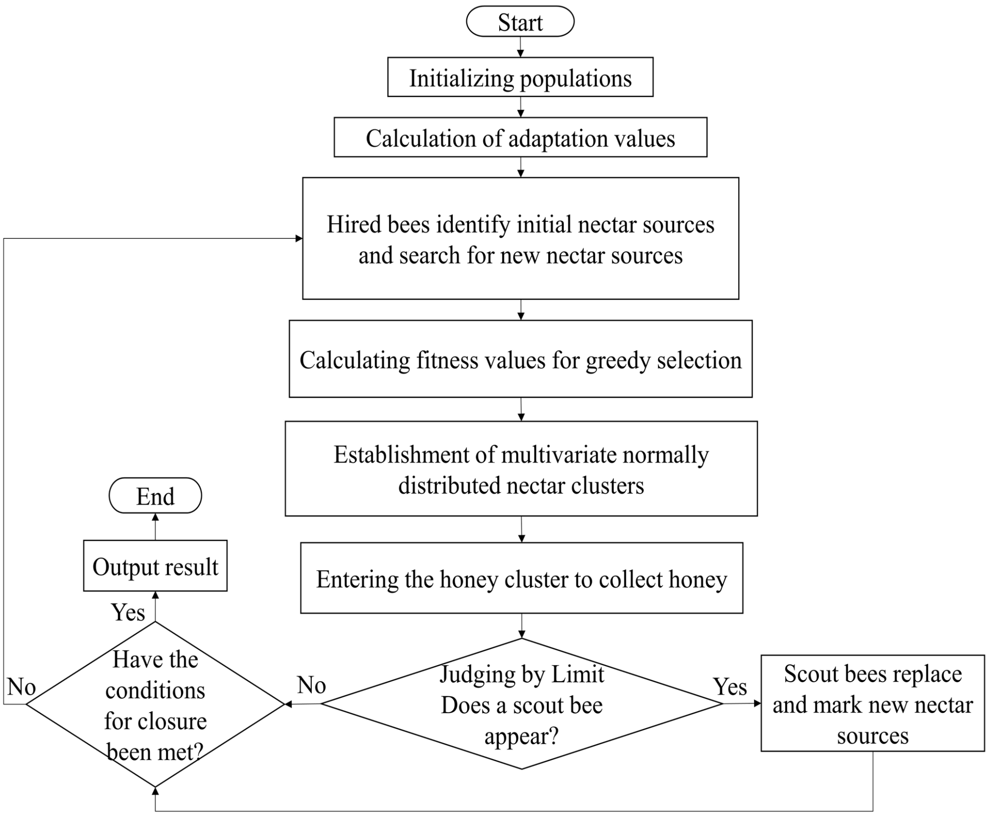

Figure 23: Flowchart of ABC-MND algorithm

5. Simulation and analysis of household electricity optimization

In order to verify the correctness of the methodology of this paper and the applicability of ABC-MND algorithm for household electricity consumption management, this section will carry out an arithmetic example simulation for the household electricity consumption optimization model based on the analysis of users' habits, and select genetic (GA) algorithm, particle swarm (PSO) algorithm, traditional artificial bee colony (ABC) and gray wolf (GWO) algorithms with good optimality seeking performance for comparison to verify the optimality seeking ability of ABC-MND algorithm under specific application environment, and finally select the final population of ABC-MND control algorithm as the proposed electricity consumption optimization scheme for this household and analyze the proposed scheme. MND algorithm's ability to find the optimal in the specific application environment, and finally, the final population of ABC-MND control algorithm is selected as the power consumption optimization scheme for the household, and the proposed power consumption optimization scheme is analyzed.

5.1. Simulation results analysis

In this paper, for household electricity optimization, simulation is carried out using ABC-MND algorithm under MATLAB 2018b platform. Comparisons are made with GA algorithm, PSO algorithm, ABC algorithm and GWO algorithm to evaluate the four aspects of convergence, electricity cost, user comfort and PAR metrics. To be fair, the model and objective function are kept constant and only the solution algorithm is changed. Each algorithm is set with a population size of 50 and 600 iterations, and 10 independent experiments are conducted to compare the average results.

In this paper, the electricity expenditure is considered as the primary objective, and the target weights of the electricity cost, user comfort and PAR indexes are set as: $\omega_1 = 0.4$, $\omega_2 = 0.3$, $\omega_3 = 0.3$ respectively, and the users can set the corresponding weight values by themselves according to their preferences. A comparison of the convergence curves obtained is shown in Figure 24:

As can be seen from Figure 24, the GA algorithm converges prematurely and falls into the local optimal solution. The PSO and ABC algorithms are slow in searching and cannot find the global optimal solution. The GWO algorithm can jump out of the local optimum, but the global search ability needs to be strengthened. The ABC-MND algorithm proposed in this paper has better global convergence, significantly improves the search ability, and can quickly converge to a more accurate optimal solution. Simulation results show that the ABC-MND algorithm outperforms other algorithms and finds the optimal electricity consumption scheduling scheme. Among them, the user's electricity cost, electricity satisfaction and PAR indexes are shown in Fig. 25, Fig. 26 and Fig. 27.

As can be seen in Figure 25, the percentage reduction in electricity cost after the user adopts the electricity consumption optimization strategies based on GA,

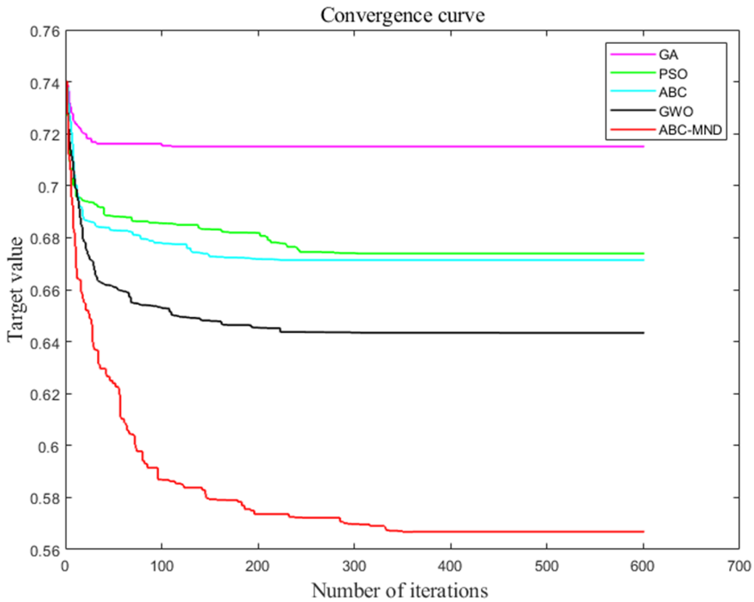

Figure 24: Convergence curves of adaptation values for different algorithms

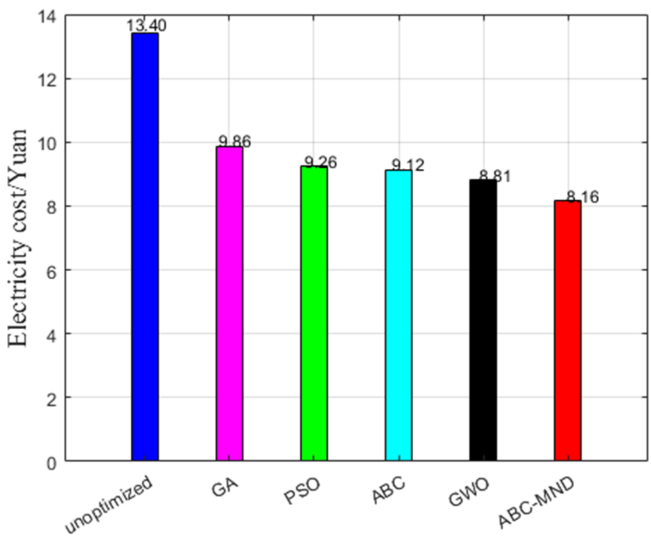

Figure 25: Electricity consumption costs for different algorithms

PSO, ABC, GWO and ABC-MND algorithms are 26.4%, 30.9%, 31.9%, 34.2% and 39.1%, respectively. Among them, the electricity consumption optimization strategy based on ABC-MND algorithm is optimal in terms of electricity cost minimization, and the household electricity cost decreases from \$13.4 to \$8.16.

The results show that the control algorithm proposed in this paper can successfully reduce the electricity cost of users and improve the optimization efficiency and cost control savings.

Figure 26 shows the satisfaction of electricity consumption under each algorithm. The GA algorithm saves electricity cost at the expense of user comfort,

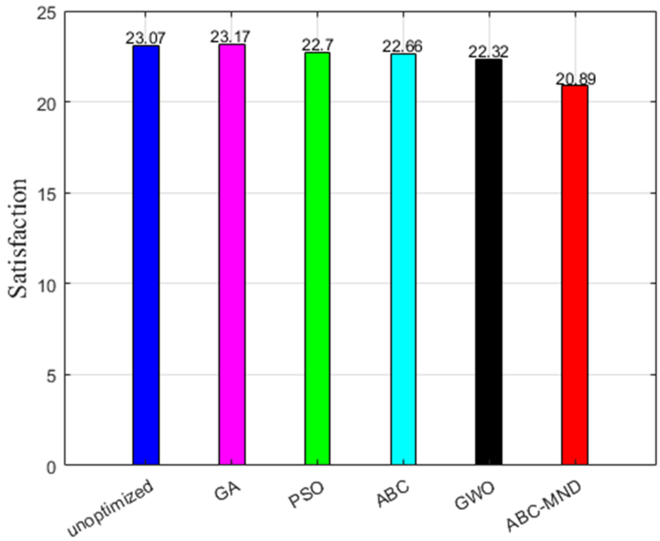

Figure 26: Satisfaction values for different algorithms

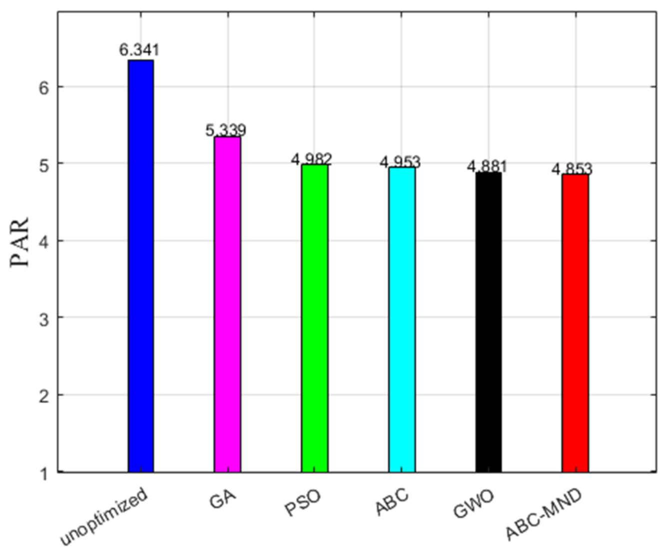

Figure 27: PAR metrics for different algorithms

while the other algorithms optimized user satisfaction is reduced, where the lowest satisfaction is achieved by the electricity optimization strategy based on the ABC-MND algorithm, i.e., the highest level of comfort in electricity consumption.

Figure 27 shows that the PAR of GA algorithm is 6.341, while the PAR of PSO, ABC, GWO and ABC-MND algorithms are 5.339, 4.982, 4.881 and 4.853, respectively. The ABC-MND algorithm proposed in this paper performs better in minimizing PAR, which can comprehensively consider all the factors to smooth the peak of electricity consumption and reduce the peak-valley difference of the power grid.

In conclusion, the ABC-MND algorithm proposed in this paper has high applicability in household electricity management and can plan a household electricity optimization scheme that meets the user's needs and satisfies the user.

5.2. Analysis of power consumption optimization schemes

In this subsection, the final population of ABC-MND control algorithm is selected as the power consumption optimization scheme for this household to be analyzed, Fig. 28 shows the initial runtime distribution, Fig. 29 shows the optimal runtime distribution of the final population based on ABC-MND control algorithm, and Fig. 30 shows the power load profile under this power consumption scheme.

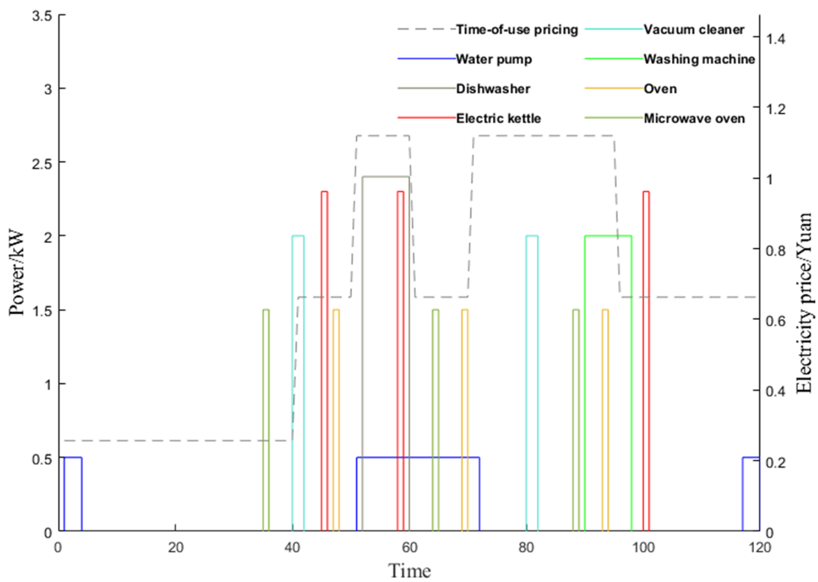

Figure 28: Initial program

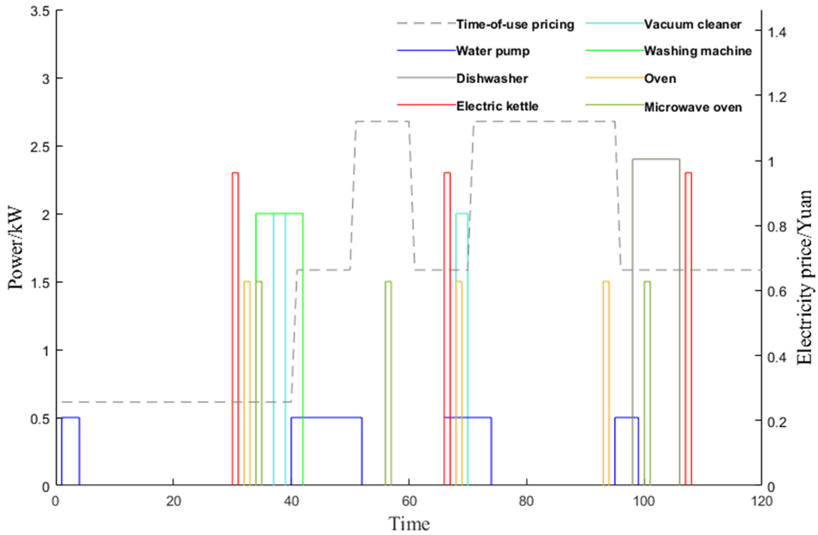

Figure 29: Power consumption optimization scheme for ABC-MND control algorithm

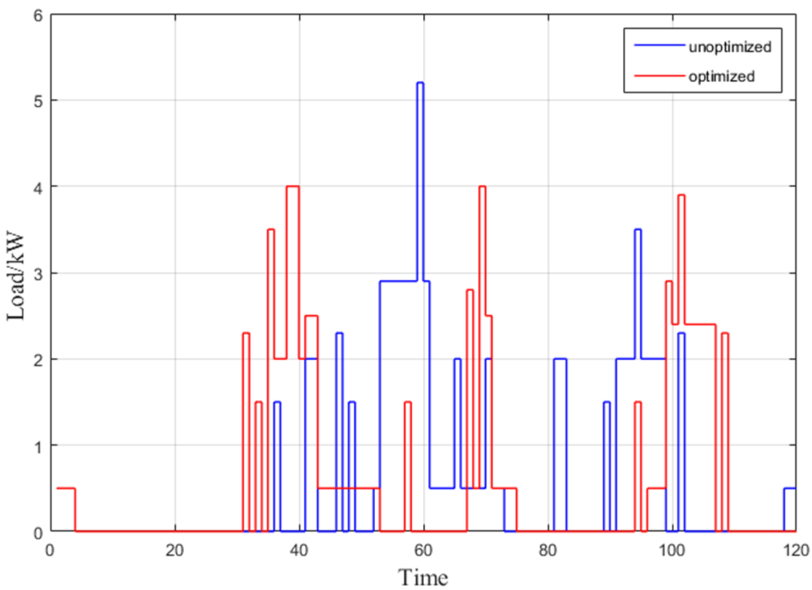

Figure 30: Optimized electrical load profile

With the ABC-MND control algorithm, the optimized electricity consumption strategy makes each electricity-using device run in different time periods. The washing machine and dishwasher were shifted from high to low electricity price periods, and both were in the user's first electricity habit zone. The vacuum cleaner was divided into 2 subtasks, both of which shifted from the high to the low tariff period and were in the tariff's first and fourth electricity habit time zones, respectively. The water pump was divided into 4 sub-tasks, and the working interval included both usual and peak tariff periods with reduced electricity costs. Oven, kettle and microwave ovens have more reasonable start-up times and power usage periods, which are in line with users' daily usage habits. In summary, most of the loads were shifted to work at times when electricity costs were low, peak electricity use was low, and user habits were prioritized. The optimized power consumption strategy reduces the peak household power consumption to 4 kW, and the power load is evenly distributed, improving the stability of the power system operation. The relationship between the cost of electricity consumption over time in a 24-hour period before and after optimization for this user is shown in Figure 31.

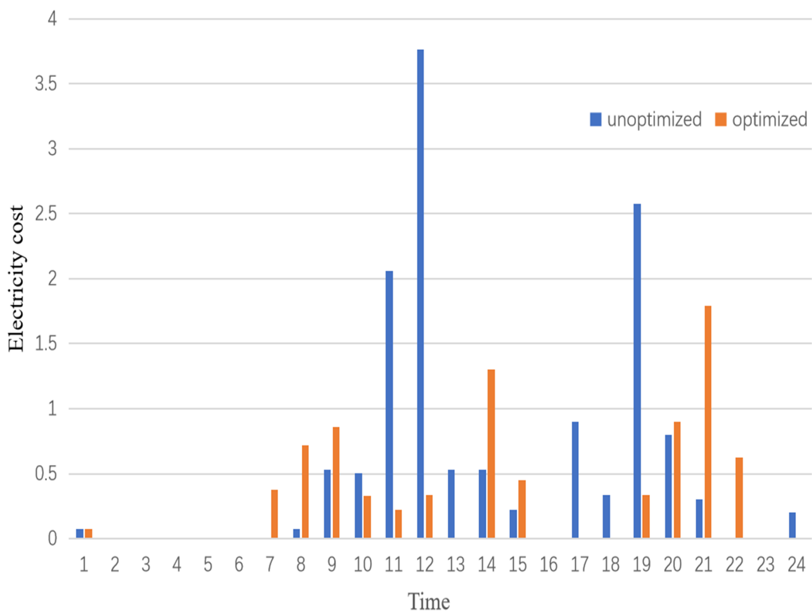

Figure 31: Comparison of power costs before and after optimization

Figure 31 shows the variation of electricity costs over time for users before and after optimization. Before optimization, users purchased large amounts of electricity during peak hours such as 11:00 p.m., 12:00 p.m., and 7:00 p.m., resulting in high electricity costs. After the algorithm optimization, it reduces the amount of electricity purchased from the grid by the user during peak hours and reduces the average daily cost of the user by purchasing electricity during the parity hours as much as possible. This not only saves electricity costs but also relieves the load on the power system during peak hours. The household electricity consumption optimization strategy developed using the ABC-MND control algorithm allows for load shifting within the constraints of the user's electricity consumption habits, which largely reduces concentrated household load usage. The comparison data of each electricity usage objective before and after optimization is shown in Table 11.

Table 11: Comparative data for various electricity consumption targets

Optimization state	Electricity cost/$	job satisfaction	*PAR* indicator
Pre-optimization	13.40	23.07	6.341
Post-optimization	8.32	20.85	4.853

Table 11 shows that the optimized household electricity cost decreased from \$13.40 to \$8.32, saving \$5.08 and 37.9% electricity cost. The value of customer satisfaction decreased from 23.07 to 20.85, indicating an increase in the comfort of electricity consumption. The PAR indicator decreased from 6.341 to 4.853, with more effective control and management of electricity consumption. The optimized solution improves on all three objectives and increases the efficiency of household electricity use. The feasibility of the electricity consumption optimization model based on user habit analysis is verified, and the customized electricity consumption scheme can control the electricity consumption cost more effectively and achieve energy saving and emission reduction.

6. Conclusions

This paper proposes a new power optimization strategy based on user habit analysis, which is more humane, efficient and intelligent. With the rapid penetration of information technology and smart technology into people's daily life, the demand of home users for the mode of electrical energy exchange has changed, and the optimization of home electricity use faces problems such as inefficiency and imbalance between supply and demand. Against the background of continuously rising electricity demand but energy scarcity, it becomes important to actively participate in electricity management and scientifically plan electricity usage. The main contributions of this paper are as follows:

First, the background and significance of the selected topic are discussed, and the current research status of related fields at home and abroad is analyzed. Secondly, the overall architecture of the home energy management system is briefly introduced, and the mathematical models of different types of loads are established. Then, a circular coordinate fitting method is proposed by mining the characteristics of users' historical electricity consumption data, analyzing users' electricity consumption habits by using a clustering algorithm, and introducing a distribution indicator to judge the dispatch type of equipment. Then, considering multiple optimization indexes comprehensively, an intelligent power consumption optimization model is established, and an improved artificial bee colony algorithm is used to solve the problem. Finally, the simulation results show that the method can significantly reduce the cost of electricity while ensuring the comfort of users.

However, this paper has some limitations, including the need for further research on multiuser coordination strategies and modeling of variable power devices. Future work should also consider the impact of real-time user information updates on scheduling plans and synthesize various uncertainties in a complex and changing environment. In conclusion, the methodology proposed in this paper provides practical and valuable insights for household power optimization and has a high potential for application and dissemination.

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