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Research on Home Energy Consumption Optimization Based on User Habit Analysis

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Abstract. *With the development of smart electricity technology and demand response, optimization of household electricity consumption behavior has become an important research element for energy saving in residential buildings. In the study of smart electricity consumption in households, the differences in users' lifestyles and their preferences for the use of various appliances can have a great impact on the results. And many existing methods need to rely on users' awareness, which does not meet the popular demand. In this paper, we propose a new method for residential load scheduling that takes into account the load characteristics of appliances and electricity consumption habits. By analyzing the household electricity consumption data set and mining the personalized needs and usage preferences of this user for various appliances, we establish an optimization model for electricity consumption behavior that combines the minimization of electricity expenses and user comfort. Finally, an improved artificial bee colony algorithm is proposed for solving the optimization model and generating a personalized dispatching strategy combined with real-time electricity pricing (RTEP) tariff. The proposed improved artificial swarm algorithm is compared with other classical algorithms, including GA, PSO, ABC, and QABC, and the analysis of cases shows that the model can effectively reduce the electricity consumption cost and ensure the customer satisfaction, and the proposed improved ABC-based algorithm outperforms other algorithms in terms of cost and user comfort.*
Keywords: Demand response, Optimized scheduling, Home power optimization, Electricity consumption habits, Improved artificial bee colony algorithm

1. **Introduction.** Nowadays, electricity has penetrated people's production and life, enterprises and residents' electricity demand is getting bigger and bigger, especially the household residential electricity consumption shows a growth trend, the increasing use of high-powered intelligent appliances and the popularity of home electric vehicles, so that the power supply cannot quickly keep up with the development needs, resulting in the increasing contradiction between power demand and supply, the peak time power demand tension and low time power demand less, resulting in energy waste. With the continuous construction of a smart grid and smart measurement system, it can improve the reliability of power supply while allowing residential customers to participate in demand response, appliance scheduling is to shift household loads from peak hours to off-peak hours, use demand-side management to schedule electricity demand in a real-time tariff environment, adjust the way household appliances use electricity, and do not perform load shedding throughout the process, thus improving electricity efficiency and reduce the cost of electricity consumption [1]. However, due to the rapid development of smart homes and unfamiliarity with tariff information, residential customers find it difficult to manually schedule these loads to work at the right periods. Therefore, home energy management systems play an important role in the residential sector for cost savings and comfortable and convenient living [2], and home energy management systems can effectively reduce household electricity expenses and improve the energy consumption of household loads while ensuring user comfort requirements [3].

Many scholars have conducted systematic and in-depth research work on smart home [4, 5], among which, the research on home electricity optimization is very extensive. The literature [6] proposes a method to reduce household electricity costs by considering electric vehicles and uninterruptible power supplies as energy storage systems in combination with real-time electricity prices. The literature [7] classifies household appliances into two categories, transferable and non-transferable, and proposes a new dragonfly algorithm for electricity consumption optimization to minimize the cost of electricity consumption. In the literature [8], a comprehensive classification of household appliances and a separate comfort assessment model for each category is developed to obtain a clear cost-comfort analysis to ensure the comfort of users during load dispatching. Currently, artificial intelligence algorithms and machine learning techniques are widely used [9, 10]. In the literature [11], an innovative appliance scheduling framework based on the fused Gray Wolf and Crow Search Optimization (GWCSO) algorithm is proposed, which has a better performance compared to other classical algorithms, including BPSO and GA. The literature [12] integrates renewable energy system (RES) and energy storage system (ESS) in a home energy management system but does not consider the installation and post-maintenance costs of RES and ESS. The literature [13] proposes a distributed mechanism and introduces the subgradient method to solve the energy optimization problem. In general, there are multiple factors to be considered for real-time problems in-home energy management systems, and multi-objective evolutionary algorithms can also be used to solve them when there is more than one objective function to achieve trade-offs between multiple problems such as electricity cost and comfort [14, 15, 16].

The analysis of customers' electricity consumption habits is important for the development of demand-side electricity optimization schemes, and currently data mining technology is mainly used to analyze customers' classification and electricity consumption habits. In the literature [17], a method for analyzing user's electricity consumption behavior for smart electricity consumption environment is proposed to cluster user loads, which can effectively distinguish users with different electricity consumption behaviors. In the literature [18], an integrated clustering approach is proposed to analyze the weekly electricity consumption data of customers and suggest the corresponding electricity consumption.

In these studies of smart home electricity use, the settings of various device usage parameters such as the type of appliance, on-time, and run-time are the basis for appliance scheduling, and these data change depending on the diversity of different users' habits. However, many studies rely on experience for this part of the work, and most users are unable to abstract their daily operating habits accurately. The lifestyles and appliance usage preferences of different households are very different, and users' electricity habits show a large inconsistency [19]. If user demand and operation preferences are not analyzed, users' electricity behavior habits may be changed during load scheduling, which will greatly reduce their comfort and may lead to energy waste in serious cases.

This paper is carried out based on such a background and will analyze the user's household electricity consumption dataset, dig out the user's electricity consumption behavior habits, and use the K-means clustering algorithm to classify each device, analyze the characteristics and usage preferences of that device, and give the constraints for the optimization of appliance operation. On this basis, an optimization model of electricity consumption behavior considering users' usage habits is established, a minimization of electricity expenditure function and a user satisfaction function is constructed, and in addition, an improved ABC algorithm based on which the model is solved is proposed. Finally, it can develop corresponding energy saving schemes according to different user groups and formulate targeted home energy optimization strategies. The general structure of this paper is organized as follows: Section 2 describes household energy management systems and user behavior habits analysis methods, Section 3 establishes the energy optimization and comfort model for the actual problem, Section 4 select an improved artificial bee colony algorithm to solve the model, and Section 5 conducts simulation experiments based on real data sets to verify the effectiveness of the proposed method, and Section 6 concludes this study.

2. **Home Energy Management System and User Habit Analysis.** An important prerequisite for home electric load dispatch is the Home Energy Management System

(HEMS), as it is an important tool for residential customers to participate in demand response, so let's first introduce the HEMS.

2.1. **Home Energy Management System.** The HEMS is to use communication technology to interconnect power generation, energy storage, power consumption and the outside world, so that electricity and information can flow in both directions to achieve real-time monitoring, intelligent processing and intelligent regulation. An ideal home energy management system is mainly composed of distributed energy, advanced measurement system, intelligent control terminal and intelligent home appliances.

(1) Energy Supply Side: HEMS has four sources of energy supply: the grid, renewable energy generation, energy storage devices, and electric vehicles.

(2) Advanced Metering Infrastructure: The Advanced Metering Infrastructure (AMI) is a control and processing system capable of collecting, analyzing, storing and transmitting household electricity consumption data, and is the core component of a home energy management system. Smart meters are the most core equipment in AMI. In addition to traditional power metering and billing functions, they also add functions such as power monitoring, data storage, and two-way communication [20], providing important technical support for home power scheduling and user demand side response.

(3) Smart Control Terminal: The smart control terminal is an essential part of the home energy management system, optimizing the operation of the electric load and the distribution of the energy supply side by analyzing and processing the electricity consumption data and environmental information obtained from sensors, smart sockets and other components.

(4) Smart Home Appliances: Smart home appliances have more advantages than traditional home appliances, which are mostly mechanical and simple execution processes. Smart home appliances make comprehensive use of advanced computer technology, Internet of Things technology, communication technology, etc., collecting and processing information through sensors and control chips, both sensitive perception, automatic adjustment, interactive intelligent control, energy saving, etc., turning users from passive adjustment to active control [21].

2.2. **Analysis of Electricity Consumption Habits.** With the diversification of society and the diverse lifestyle of each household, users also have different usage habits for different appliances, which may change from time to time. To reduce the discomfort of users' participation in optimal scheduling of devices and to maximize the satisfaction of users' daily usage habits, mining the usage habits of each appliance from the household electricity data set and defining the usage characteristics of that appliance are the prerequisites of this study. The scheduling parameters of the appliance will be obtained here, including the scheduling type of the appliance, the optimal start time, the optimal shutdown time, the scheduling time range, and the operation duration. In this paper, we will analyze the usage data of various appliances of users over one year, which include:

(1) Scheduling type of appliance. The household electricity use dataset is analyzed to mine the working duration of the device each time and the Coefficient of Variation ($C.V$) is introduced to determine the degree of dispersion of the device duration. The smaller the $C.V$ indicates that the working duration is basically fixed for this device, while interruptible devices can be temporarily interrupted resulting in variable continuous working duration and relatively large $C.V$ values, which are used to define whether the device is a load for interruptible use. The $C.V$ is calculated as in Equation 1.

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

In Equation 1, X_i is the operating time of the i-th operation of the device; n is the total number of operations of the device.

(2) Optimal start-end time. The Optimal start-end time is the most satisfactory start time and shutdown time for the appliance, and as an important parameter to evaluate user satisfaction, the frequency distribution of the users' start time and shutdown time for the appliance will be counted from a large amount of data, and the highest frequency-time point will be taken as the best start time and shutdown time. In the process of scheduling appliance, we will try to generate work schedules close to the Optimal start-end time to minimize the discomfort caused to users by appliance scheduling.

(3) Scheduling time range and electricity consumption habits. The scheduling time range is the usage time range limit that meets the user's usage habits, and the appliance scheduling is not allowed to exceed this range. In this paper, we will use the K-means algorithm to cluster and analyze the turn-on moments of appliances within a year, then use the elbow method to get the most suitable number of clusters, and consider that a class cluster represents a kind of electricity usage behavior habit, and then extract the corresponding scheduling time range.

The K-means clustering algorithm uses distance as the evaluation index of similarity, and generally uses the Euclidean distance for the distance between two sample points to measure the distance, which is calculated as shown in Equation 2. The data with similar characteristics are classified in the same set by approximating the sum of the minimum distance between each sample and the cluster center to which it belongs through multiple iterations.

$$\mathrm{d}\left(x_i, x_j\right) = \sqrt{\left(x_i - x_j\right)^T \left(x_i - x_j\right)} \tag{2}$$

Where: x_i denotes the i-th data point.

3. Construction of Energy Consumption Optimization Model.

3.1. Classification and Modeling of Household Load.

The electricity load is an indispensable part of the residence. In general, in addition to the necessary electricity demand, the user hopes to transfer the load from the time period with higher electricity price to the time period with lower electricity price as much as possible. Throughout the device scheduling process, it is important to determine the demand information of the load, and each device involved in the scheduling must be defined as a device type. They can be divided into three categories: interruptible devices, non-interruptible devices, and common devices. Ordinary devices are non-regulable devices such as lights and refrigerators, which are not involved in energy optimization management.

In this paper, the optimization of the controllable power load takes the day as the scheduling unit. Considering that most electrical equipment does not limit the working time to a certain complete hour, and some electrical appliances work for a short time, in order to reduce the error caused by the calculation, this paper divides a day into 120 hours each hour is divided into 5 equal time periods, and assuming that the minimum running time of any household appliance load is 12 minutes, the excess of 12 minutes is regarded as a multiple of 12, and the power of electrical equipment in each time period remains unchanged.

The schematic diagram of interruptible appliance power consumption is shown in Figure 1, which can delay or interrupt the operation, its power consumption interval can be segmented and discontinuous, Under the condition of ensuring the workload, it can be temporarily interrupted in the operation state to achieve the scheduling strategy.

Constraints:

$$t_{start} \geq \alpha_i \tag{3}$$

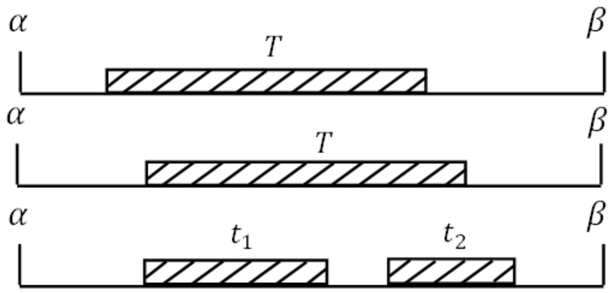


FIGURE 1. Interruptible appliance

$$t_{end} \leq \beta_i \tag{4}$$

$$\beta_i - \alpha_i \geq \ T_i \tag{5}$$

$$x_i^k = \begin{cases} 0, & if\ appliance\ is\ OFF \\ 1, & if\ appliance\ is\ ON \end{cases} \tag{6}$$

$$\textstyle\sum_{k=\alpha_i}^{\beta_i} x_i^k = T_i \tag{7}$$

The schematic diagram of non-interruptible load power consumption is shown in Figure 2. Only delayed operation is possible, and once the power-using appliance starts running, it will keep running continuously until the power consumption task is completed.

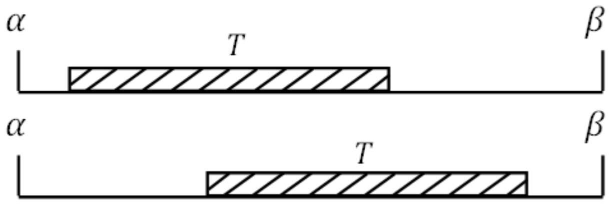


FIGURE 2. Non-Interruptible appliance

Constraints:

$$t_{start} \geq \alpha_i \tag{8}$$

$$t_{end} \leq \beta_i \tag{9}$$

$$\beta_i - \alpha_i \geq \ T_i \tag{10}$$

$$x_i^k = \begin{cases} 0, & if\ appliance\ is\ OFF \\ 1, & if\ appliance\ is\ ON \end{cases} \tag{11}$$

Where, x_i is the operation state of appliance i at time k ; t_{start} is the actual start time of the appliance; t_{end} is the actual end time of the appliance; β_i is the latest end time allowed; α_i is the earliest allowed start time; T_i is the appliance running time.

3.2. **Electricity Cost Function.** The objective of the electricity cost function is to minimize the electricity expenditure without affecting the electricity demand, so the electricity cost is used as the main objective for the optimal control of electricity consumption, and the electricity cost of all devices in the household for one day is:

$$C = \textstyle\sum_{k=1}^{t} \sum_{i=1}^{n} x_i^k * EP(k) * P/5 \tag{12}$$

Where: $EP(k)$ is the electricity price in the k-th period; P is the rated power of the appliance; n is the total number of appliances; t=120.

3.3. **Satisfaction Function.** User satisfaction, also called comfort of use, refers to the impact of changes in electricity plans or habits on the user, although the user sets an effective working range time period for each electricity device, the user usually wants these devices to complete their electricity use within their most satisfactory working time period and with the minimal waiting time. The closer the scheduling strategy is to the user's habits, the higher the user's satisfaction [22].

This paper proposes different satisfaction measures based on the power consumption characteristics of two types of controllable power devices (interruptible and non-interruptible appliance).

The satisfaction measure of non-interruptible appliance is defined as the relative distance between the actual start time of the appliance and the ideal start time set by the customer, and customer satisfaction is highest if the task starts at the ideal time.

$$f_1 = \frac{|t_{\text{start}} - t_{\text{op}}|}{\beta_i - \alpha_i - T_i} \tag{13}$$

Where: t_{start} is the actual start time of the appliance; t_{op} is the optimal start time of the appliance; α_i is the earliest allowable start time of appliance i; β_i is the latest allowable end time of appliance i; T_i is the operating time of appliance i.

The satisfaction measure of an interruptible appliance is defined as the time distance between the actual running time of the interruptible appliance and the theoretical time spent during the operation of the appliance without interruptions, taking into account the relative distance between the actual end time of the electricity-using appliance and the ideal end time set by the user. The user satisfaction is highest if there are no interruptions and the task ends at the user's ideal time.

$$f_2 = \frac{(t_{\text{end}} - t_{\text{start}} - T_i) + \left|t_{\text{end}} - t_{\text{opend}}\right|}{\beta_i - \alpha_i - T_i} \tag{14}$$

where: t_{end} is the actual end time of the appliance; t_{opend} is the optimal shutdown time of the appliance.

Ultimately, the user satisfaction function F, whose expression is Equation 15.

$$F = \sum_{p=1}^{a} f_1^p + \sum_{q=1}^{b} f_2^q \tag{15}$$

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

3.4. **Electricity Use Strategy Objective Function.** In this paper, while providing users with energy optimization solutions, we fully consider users' electricity consumption habits, so we take into account two factors: minimizing electricity expenses and adjusting appliance usage to the moment when real-time electricity prices are lower; ensuring user satisfaction and scheduling without changing users' original electricity consumption habits as much as possible.

Obviously, these two factors are in conflict with each other, and one of them is often sacrificed in the optimization process. Therefore, multiple objective function values are normalized when establishing the objective function of the energy-saving strategy considering user habits, and the final objective function expression is Equation 16.

$$M = w_1 \frac{C - C_{min}}{C_{max} - C_{min}} + w_2 \frac{F - F_{min}}{F_{max} - F_{min}} \tag{16}$$

By setting different weighting factors to take the importance of electricity bills and satisfaction with electricity consumption.

4. **Model Solution Based on Improved Artificial Bee Colony Algorithm.** Optimization of the objective function for home energy consumption based on user habits is a nonlinear 0-1 programming problem containing multiple constraints, and the result of the optimization is to reduce the electricity bill as well as to ensure the satisfaction of the users. To solve these problems, swarm intelligence algorithms such as genetic algorithm (GA) [23], particle swarm optimization algorithm (PSO) [24], and artificial bee colony algorithm (ABC) have been used for feature selection. Among them, the ABC is an artificial intelligence algorithm proposed by Turkish scholar Karaboga [25] in 2005 to search for optimal solutions by simulating the foraging behavior process of bees, and the problem to be solved is transformed into individual bees with honey source information by appropriate encoding, in which recruiting bees, sharing honey source information, and abandoning honey sources constitute the optimal search operation of ABC algorithm. The ABC algorithm has the advantages of parallel computing, strong search capability, and few control parameters, which can effectively solve the multivariate function optimization problem [26], but the ABC algorithm has the defect of converging on the local optimal solution earlier, and although the algorithm has good search capability, it is under-exploited and weak in local search capability. Therefore, in this paper, an improved artificial bee colony algorithm is proposed for the constrained optimization problem, and the improved artificial bee colony algorithm is used to solve the objective function. The specific idea and process are as follows.

(1) Initialization of the bee colony. Like the classic ABC algorithm, the initial SN populations are generated using the random initialization method, as follows:

$$X_i^d = X_{\min}^d + \operatorname{rand}(0,1) \cdot \left(X_{\max}^d - X_{\min}^d\right) \tag{17}$$

Where: $i \in \{1, \ldots, SN\}, d \in \{1, \ldots, D\}, X_{\max}^d$ and $X_{\min}^d$ are the upper and lower bounds of the d-th dimension of the search space.

(2) Employed bee phase. Employ bees to search and generate a new honey source in a given space according to Equation 18:

$$x_{i+1} = x_i + \varphi\left(x_i - x_j\right) \tag{18}$$

Where, x_j represents a neighborhood honey source, which is a randomly selected honey source that is not equal to i among the total honey sources, φ is a random number taking values in [-1,1], and a greedy selection method is used after the new nectar source is generated, and the nectar source with high adaptation will replace the old one.

(3) Onlooker bees phase. In classical ABC, the following bees are employed at this stage to search for new nectar sources, and roulette is used according to the abundance of nectar sources, with a higher probability that the nectar source with a large adaptation value will be selected, and the following bees will harvest the nectar source after being selected. However, when the number of populations reaches a large number, the probability of belonging to each nectar source differs very little, and good nectar sources cannot be effectively selected by the roulette method, and the effect is equivalent to random search, which greatly reduces the exploitation ability of ABC. To further improve the exploitation capability of ABC, some literature uses the global optimal solution to lead bees to search for new nectar sources through an elite guidance mechanism [27], however, this strategy is prone to fall into local optimal solutions when dealing with complex problems, leading to poor final results.

In order to solve such problems, in this paper, we will command the following bees to collect honey in the vicinity of the optimal honey source, introduce the concept of multivariate normal distribution, and randomly generate a cluster of honey sources conforming to the multivariate normal distribution in the vicinity of the optimal honey source, the closer the location of the optimal honey source is generated, the more honey sources and the higher the density, where the generated honey sources $X = [x_1, x_2, \ldots, x_d]$ satisfy the following conditions:

$$X \sim N(\mu, \Sigma) \tag{19}$$

Where:

$$\mu = E(X) = (\mu_1, \mu_2, \ldots, \mu_k) \tag{20}$$

$$\Sigma_{i,j} = \mathrm{Cov}\,(x_i, x_j) \tag{21}$$

μ represents the mean value, and this study will take μ as the global optimal solution, $\mu = x_{best}$.

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

Taking the 3-dimensional space as an example, the effect of the nectar cluster produced at [1,1,1] as the center of the nectar source conforming to the multivariate normal distribution is shown in Figure 3.

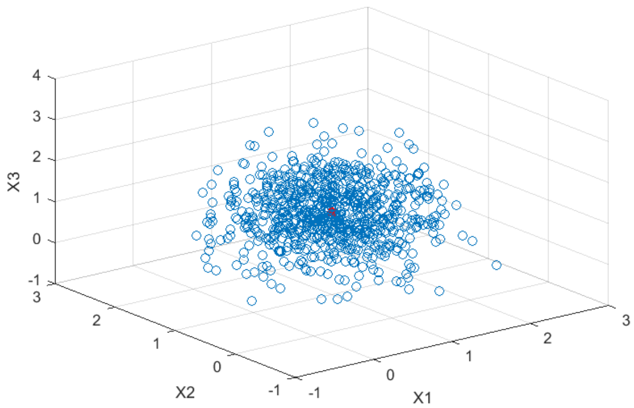


FIGURE 3. Three-dimensional nectar cluster

Then, a nectar source was randomly selected as the target nectar source from the nectar source group that met the normal distribution and the following bees are directed to collect nectar here, making ABC retain the nature of elite guidance, enhancing local exploitation while maintaining the diversity of the colony and preventing premature convergence. Next the following bees use Equation 22 to find new nectar sources, where they are guided using the optimal nectar source, and finally follow a greedy selection method to retain the high-quality nectar source.

$$x_{i+1} = x_i + \varphi \cdot (x_{best} - x_j) \tag{22}$$

Where: x_{best} represents the global optimal solution

(4) Scout bee phase. When the number of counters is greater than a predetermined number and no better nectar source is found, this nectar source is discarded and the employed bee is transformed into a scout bee, and the scout bee in the original ABC will re-initialize this source using Equation 17 to generate a new source at random. In this paper, we adopt a different strategy to explore and exploit the search space, let the scout bee absorb the information of multiple good bees in the colony, use Equation 23 to re-initialize this honey source, guide the honey source to generate at a better position,

and appropriately enlarge the perturbation magnitude, i.e., α value, to avoid falling into a local optimum.

$$x_i = x_i + \alpha \cdot (x_{best} - \alpha \cdot M) \tag{23}$$

$$M = \frac{(x_1+x_2+x_3)}{3} \tag{24}$$

Where: x_1, x_2, x_3 are the top three nectar sources sorted by fitness optimum, and α is taken as [0, 2] uniformly distributed random numbers.

5. Experiment and Analysis of Algorithms.

5.1. Analysis of Electricity Consumption Habits. Simulation experiments were conducted using the UK Domestic Appliance Level Electricity (UK-DALE) dataset published by the UKERC Energy Data Centre [28], an open access dataset from the UK that records the electricity demand of each device and the whole household in a UK household approximately every 6 seconds. In this calculation, several types of commonly used appliances are selected for analysis, and six controllable appliances: vacuum cleaner, toaster, dishwasher, washing machine, kettle and water pump are selected to analyze the electricity consumption data over a year to derive the electricity consumption habits.

Taking the usage data of washing machines within one year from 2014-2015 as an example, Figure 4 shows the graph of all daily load curves of washing machines during one year.

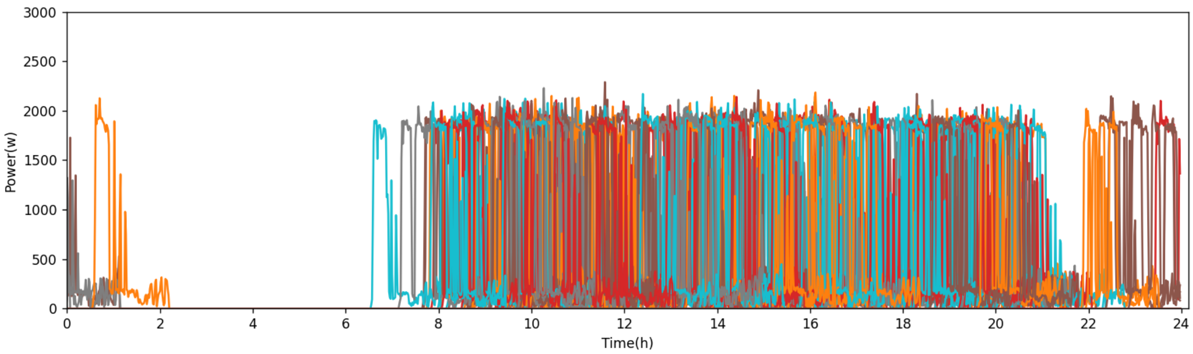
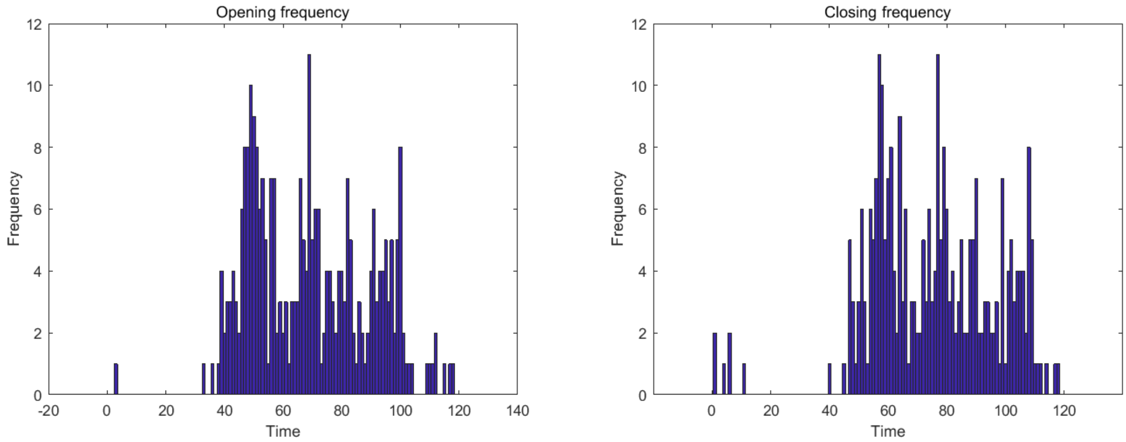


FIGURE 4. Washing machine daily load curve

Figure 5 show the information of the time when the washing machine is turned on and off in a year, from which we can learn that the user turns on the washing machine most frequently in the 86th period, that is, from 17:12 to 17:24, and often turns off the washing machine in the 94th period, that is, from 18:48 to 19:00. This is the optimal start-end time for the washing machine.

In this paper, we use the elbow method to get the most suitable cluster number k and define a class cluster to represent an electricity usage habit, as shown in Figure 6. When k=3, the distortion of the cluster is greatly increased and the drop of SSE is sharply decreased. Therefore, the optimal number of clusters k is set to 3, indicating that the washing machine in this series has 3 intervals of usage habits, and the K-means clustering algorithm is used to analyze the 3 usage time ranges of this appliance, as shown in Figure 7.

It can be seen from Figure 7 that after clustering, the usage habits of users are divided into three categories, which are divided into: electricity usage habits 1 is [0, 60], that is, 00:00 to 12:00. Electricity usage habit 2 is [61, 84], that is, from 12:00 to 16:48. Electricity usage habit 3 is [85 , 120], that is, from 16:48 to 24:00.



(a) Open Frequency (b) Close Frequency

Figure 5. Running frequency

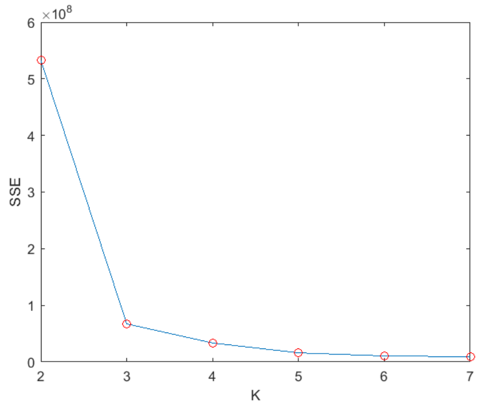


Figure 6. Clustering bias for different K values

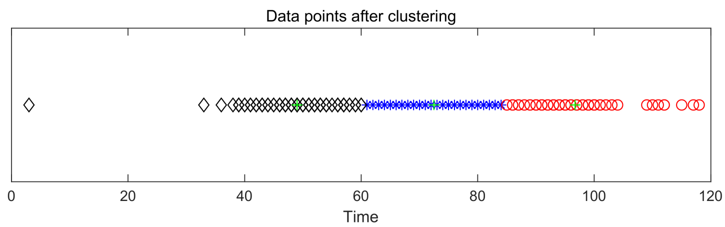


Figure 7. Clustering Results

In addition, Count the continuous running time of the washing machine in this family every time it is turned on in a year, and the results are shown in Figure 8 the $C.V$ was calculated for the continuous working time of the washing machine, and the $C.V$ value was found to be 0.1893, which means that the working duration of each time does not fluctuate much, and it can be seen from Figure 8 that the continuous working time of the washing machine is around 100 minutes each time, so the dispatching type of the washing machine is judged to be a non-interruptible device, and the working duration of each time is basically fixed, and the working interval can be shifted during the working process but

It cannot be temporarily interrupted. The $C.V$ and scheduling types of the remaining appliances are shown in Table 1. The scheduling parameters of each appliance analyzed are shown in Table 2.

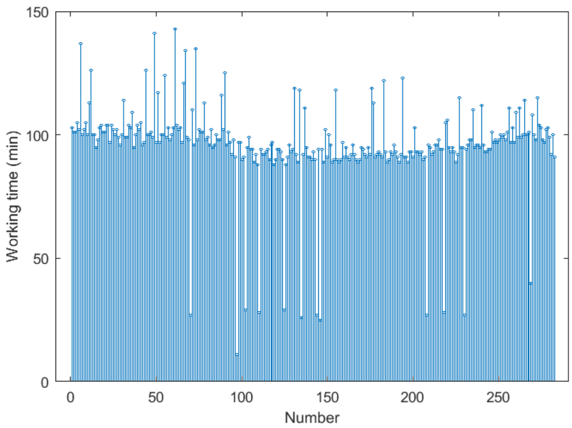


FIGURE 8. Washer Duration

TABLE 1. C.V-Value

Appliances	Washer	Dishwasher	Toaster	Kettle	Water pump	Vacuu
C.V	0.1893	0.1802	0.2279	0.4311	1.7929	0.893
Type	Non-interruptible	Non-interruptible	Non-interruptible	Non-interruptible	interruptible	interrup

TABLE 2. Appliance scheduling parameters

Category	Appliances	Habit	Operation Start-End Time	Optimal start time	Optimal closing time	Power (kW)	Duration (Minutes*Task)
Non-interruptible	Washer	Habit 1	00:00-12:00	09:48	11:24	2	96*1
		Habit 2	12:00-16:48	13:48	15:24		
		Habit 3	16:48-24:00	20:00	21:36		
	Dishwasher	Habit 1	08:00-12:48	08:48	11:00	2.4	96*1
		Habit 2	10:48-19:12	13:12	15:00		
		Habit 3	19:12-24:00	21:48	23:24		
	Kettle	Habit 1	00:00-10:24	07:24	07:36	2.3	12*3
		Habit 2	10:24-15:36	12:12	12:24		
		Habit 3	15:36-24:00	17:36	17:48		
	Toaster	Habit 1	00:00-11:00	07:48	08:00	1.5	12*3
		Habit 2	11:00-18:48	12:36	12:48		
		Habit 3	18:48-24:00	19:36	19:48		
Interruptible	Water pump	Habit 1	07:36-12:48	09:12	12:48	0.5	312*1
		Habit 2	12:48-15:00	13:24	14:12		
		Habit 3	15:00-20:24	18:36	19:12		
	Vacuum	Habit 1	00:00-13:12	10:24	11:36	2	48*1
		Habit 2	13:48-16:24	15:12	16:24		
		Habit 3	16:24-24:00	17:00	20:24		

5.2. **Example Analysis of Optimization Model.** The improved ABC algorithm for solving the model is implemented based on MATLAB R2018b. The proposed improved ABC algorithm and the GA, PSO, classical ABC, and QABC algorithm [29], are simultaneously set to run 10 consecutive cycles with a population size of 80 and an iteration number of 150, and the final results are averaged and compared. In this case, the Real-time electricity prices information is taken from the literature [30].

The evaluation of the convergence speed of each algorithm is shown in Figure 9.

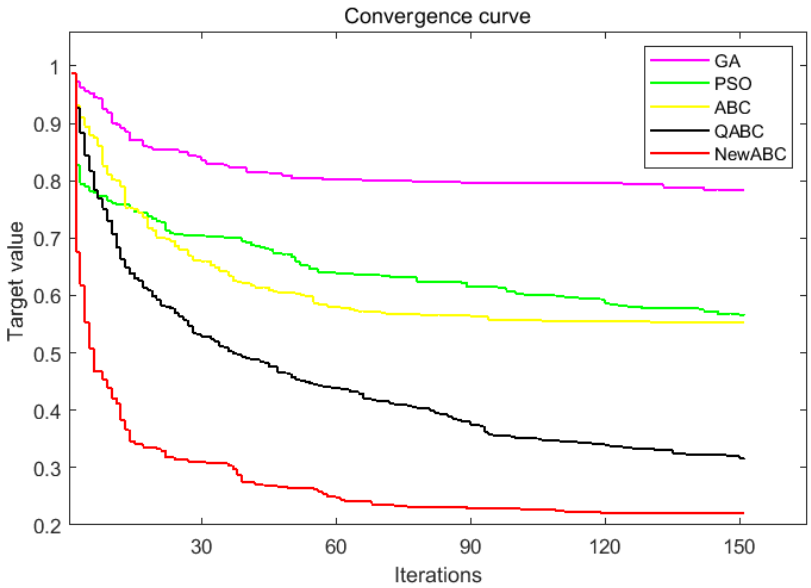


Figure 9. Washer Duration

As can be seen from Figure 9, the simulation results show that the improved ABC algorithm outperforms the GA, PSO, ABC and QABC algorithms in terms of optimization performance: it improves the search capability of the algorithm, speeds up the convergence speed and converges to a more accurate optimal solution. Among them, the user's electricity cost and electricity satisfaction results are shown in Figure 10 and Figure 11.

As can be seen in Figure 10 and Figure 11, the proposed strategy based on the Improved ABC algorithm, which optimizes household electricity consumption while ensuring customer satisfaction, outperforms energy management strategies based on other algorithms in terms of electricity cost minimization and satisfaction with electricity consumption, with a decrease in household electricity costs from 273.51 cents to 167.87 cents per day. The percentage decreases in electricity expenses based on GA, PSO, ABC, QABC, and Improved ABC algorithms were 35.6%, 36.4%, 36.9%, 38.1%, and 38.6%, respectively, and in addition, the electricity arrangement derived based on the Improved ABC algorithm was the most consistent with customer habits and optimal for customer comfort.

The distribution of the electrical load for the day before and after the scheduling of each algorithm is shown in Figure 12. The original electricity consumption plans of six representative controllable appliances in this household are optimally scheduled, and the optimal operation time distribution based on the improved ABC algorithm is shown in Figure 13.

From Figure 12 and Figure 13, it can be seen that after the optimization of scheduling by the algorithm in this paper, all electrical appliances are arranged to operate in the time period when the electricity price is lower as far as possible, and the usage habits of customers are satisfied to the greatest extent.

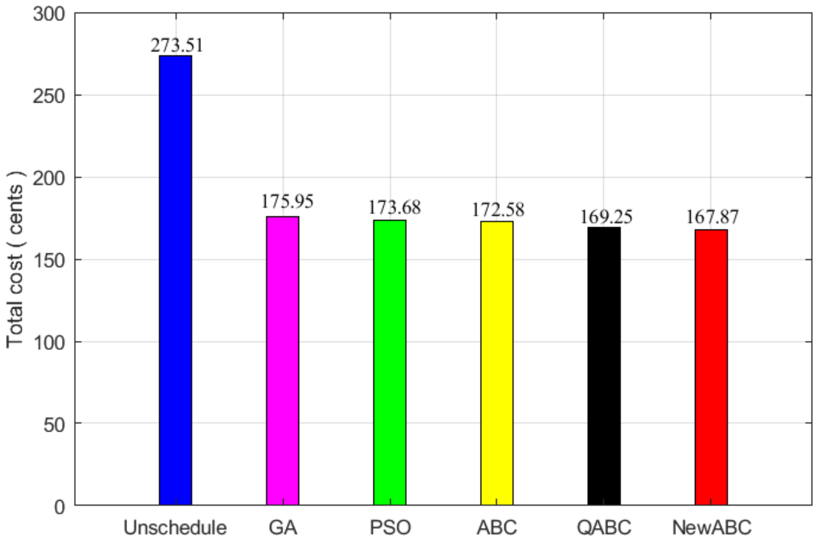


FIGURE 10. Washer Duration

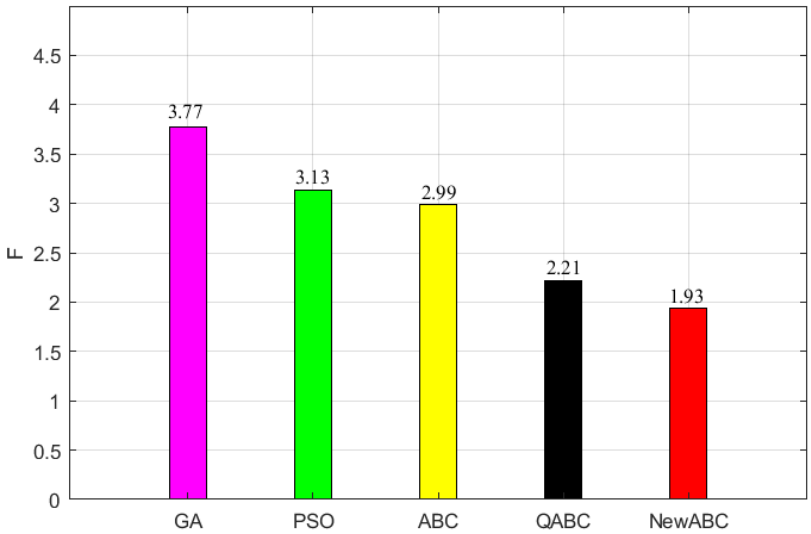


FIGURE 11. Washer Duration

The experimental results validate the effectiveness of the proposed algorithm and the new energy optimization model.

6. **Conclusion.** In this study, based on users' electricity consumption habits in the environment of real-time electricity tariff, a relevant numerical analysis was conducted using real household electricity consumption data set. And the load data of several commonly used appliances were analyzed using the K-means clustering algorithm to obtain the load characteristics and usage preferences of different devices, and to give the constraints for home appliance operation optimization, based on which, a household energy consumption optimization model considering electricity consumption habits and minimizing electricity expenses is proposed. In addition, an improved ABC algorithm is designed to solve the

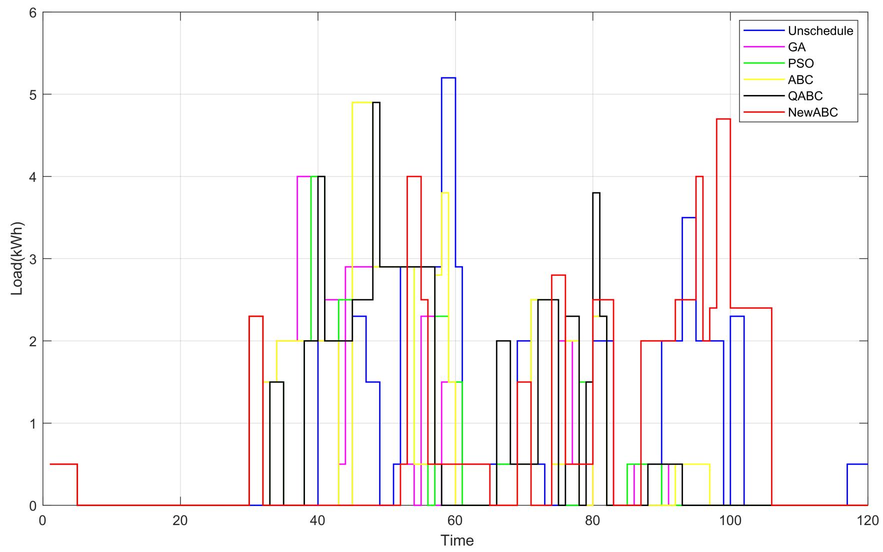


FIGURE 12. Washer Duration

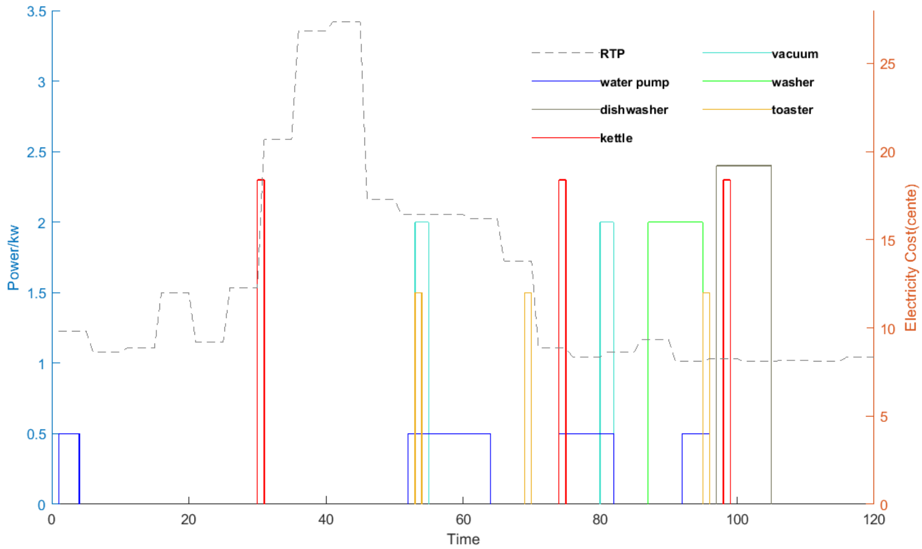


FIGURE 13. Washer Duration

model and compared with GA, PSO, ABC, and QABC algorithms. Finally, it is verified by simulation that the proposed algorithm outperforms other algorithms in terms of cost and user comfort. The new model of energy optimization based on user habits can develop corresponding energy saving schemes according to different user groups, provide personalized household load scheduling services, give reasonable power consumption arrangements, guide equipment power consumption toward low tariff periods, and effectively reduce power consumption costs while ensuring power consumption comfort.

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