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# Household Energy Demand Management Strategy Based on Operating Power by Genetic Algorithm

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**ABSTRACT** Effective and adaptable household energy management system needs to be established to promote and implement demand response projects in smart grids. The current household energy demand management strategy cannot provide users with a choice to ensure user comfort, its time sampling accuracy is not high enough, and the operation using the rated power results in a large deviation from the actual cost. In order to solve these problems, this paper proposes an optimization control strategy to achieve the minimum electricity cost based on the user response, equipment operating power, and dynamic pricing. The genetic algorithm is used for calculating the optimal operating parameters of each equipment by using the operating power. The correctness and the high accuracy of the algorithm are verified by comparing with the loop search optimization algorithm. The results show that the daily electricity cost is reduced by 29.0%, and the peak-to-average ratio is reduced by 36.2% after adopting the proposed strategy.

**INDEX TERMS** Demand response, household energy demand management strategy, genetic algorithm, operating power, user comfort.

## NOMENCLATURE

| | |
|---|---|
| $A$ | the equipment used in the optimization strategy |
| $F_{\text{cost}}$ | the daily electricity cost |
| $N$ | the number of household electrical equipment |
| $M_i$ | the number of operating cycles of the $i$-th equipment |
| $P_i^j(t)$ | the power change with time of the $i$-th equipment in the $j$-th action cycle, the unit is kW |
| $t$ | the time, the unit is minute |
| $\lambda(t)$ | the electricity price at time $t$, the unit is \$/kW · h |
| $T_{\text{set,min}}$ | the allowable indoor minimum temperature set by the user |
| $T_{\text{room}}$ | the actual indoor temperature |
| $T_{\text{set,max}}$ | the allowable indoor maximum temperature set by the user |
| $t_{bj}$ | the earliest opening time tolerable during the $j$-th action cycle time |
| $t_{ej}$ | the latest opening time tolerable in the $j$-th action cycle time |
| $t_{dj}$ | the working time in the $j$-th action cycle |
| $t_{pj}$ | the preferential opening time tolerable in the $j$-th action cycle |
| $t_{\text{final},j}$ | the optimal opening time of the equipment in the $j$-th action cycle |
| $Q_{\text{out}}$ | the energy needed to exchange heat $Q_{\text{in}}$ from the household |
| $W_{\text{in}}$ | the electric energy consumed by air conditioner |
| $P_t$ | the power at the time $t$ |
| $p_{i,t}$ | the power, where the first subscript indicates the name of the household equipment, and the second subscript indicates the time period, for example, $p_{i,3}$ is the power of the $i$-th equipment at the 3rd minute |

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## I. INTRODUCTION

Intelligent electricity terminal consumption has become one of the development trends of smart grids. The key to realizing intelligent electricity consumption is to establish a convenient and reliable interaction between power suppliers and consumers. The demand response (DR) is a prerequisite for achieving this goal. According to the definition given by the International Energy Agency in 2003, all factors responsible for variation in the level of power demand over a period of time, that is, the total amount of electricity consumption, are demand response behaviors [1]. The household energy management system (HEMS) is an extension of the smart grid. By adopting HEMS, users can better participate in implementing demand response projects and schedule the usage of household appliances [2].

At present, the household energy demand management strategy (HEDMS) has been studied in some literatures. The algorithms applied in HEDMS include mixed integer optimization algorithms, particle swarm optimization (PSO), game theory, genetic algorithms (GA), etc. Reference [3] used the mixed integer nonlinear optimization algorithm to plan the household electricity consumption under the conditions of time-of-use electricity price and incentive policy, and proved users can save more than 25% of electricity cost (EC), by ignoring the fact that equipment power is changing with time. Reference [4] introduced the PSO into energy-efficient buildings to minimize the conflict between the power consumption and the user comfort, but only considered the illumination and temperature control equipment in the building. In [5], the binary backtracking search algorithm was applied to optimize the timetable of household electrical equipment. The algorithm showed the higher energy-efficiency compared with the PSO algorithm but ignored the user comfort. Reference [6] studied the game theory between user behaviors and the electricity price policy, and adopted a distributed algorithm to reduce the peak-to-average ratio (PAR) and the EC in the system, without considering the user comfort. In [7], a heuristic scheduling optimization algorithm based on the genetic harmony search was used to evaluate the single-user and the multi-user separately with the main indicator EC, the sampling time was one hour and did not give user the option to actively choose the equipment. In [8], the equipment information and the user personal habits were uploaded to the knowledge base in the form of questionnaires. The knowledge base classified and analyzed the behavior of each user, and then recommended more reasonable behaviors to users, but had no quantitative calculation. Reference [9] evaluated the application effects of the GA and the artificial fish swarm algorithm in the HEDMS. Under the premise of real-time price and without considering the user comfort, the two algorithms reduced the total EC by 21% and 30% respectively, but ignored the fact that equipment power is changing with time. Reference [10] used an equipment scheduling strategy with a price prediction model, combining real time price (RTP) with slope block rates, and using the actual hourly price adopted by the Illinois Power Company with sampling time of one hour. The results showed that the EC and PAR can be reduced. Reference [11] used data-driven energy management based on Bayesian optimal algorithm which reformulated the economic dispatch problem without considering the user comfort and the sampling time was 30 minutes. Reference [12] used stochastic optimization and robust optimization, which were solved by mixed-integer linear programming. The results showed that the EC were reduced by 26.63% and 24.33%, respectively. However, the sampling time was 1 hour and the user could not actively choose the equipment. In summary, the above research results show that HEDMS can effectively reduce the daily EC and PAR, and has an important application value in smart grids.

Although many research achievements in HEDMS have been obtained, the following problems still need to be addressed.

(1) All equipment is participating in the program by default in most strategies, and the user is unable to choose the equipment independently, which will cause the equipment that the user does not want to participate in the plan to be scheduled. This is inconvenient for the user and affects the user's autonomy. Hence, it needs to propose a strategy to properly address the user inconvenience to encourage them to participate in the DR [13].

(2) Most of the strategies use the rated power of the equipment when planning the electrical equipment. However, the power of some equipment changes in real time in actual operations, therefore the obtained result is not optimal, which will increase the daily EC [14].

(3) Most of the strategies adopt a sampling time of 15 minutes, 30 minutes, or one hour, which will not reflect the real-time operation of the equipment well, and the control strategy calculation results deviate from the optimal.

In view of the above problems, this paper presents an HEDMS by using a genetic algorithm (GA) based on the operating power whose the sampling time is 1 minute. Users can participate in the demand response plan on their own and can reduce the EC. Based on the user response and the operating power, the minimum EC is achieved and the calculation time is greatly reduced. The structure of the article is arranged as follows: Section II introduces the frame of the HEDMS, establishes the optimization model of the HEDMS and the model of the household equipment; Section III adopts the GA to optimize the specific parameters to obtain the opening time of the equipment $t_{\text{final},j}$, and verifies the algorithm by comparing with the results calculated by a loop search optimization algorithm; Section IV verifies the strategy by typical cases.

## II. HOUSEHOLD ENERGY DEMAND MANAGEMENT STRATEGY

The HEDMS aims to ensure the user comfort and minimize the daily EC, and use a simple task-by-step optimization search method for each power equipment as reference. The power curve and the EC of all household equipment before and after using the optimal control strategy are compared and analyzed, the effectiveness and feasibility of the algorithm are verified. The advantages of the strategy given in this paper are as follows: (1) The working time of household electrical equipment is set according to the user's convenience, meanwhile users can also choose the equipment to participate in the DR. (2) The HEDMS proposed in this paper avoids the calculation of equipment that does not participate in the DR, which improves the calculation speed of the algorithm. (3) The operating power data of the equipment can be acquired by the model simulation or directly analyzing the historical operation data. The algorithm contains the data extraction function over the time span of 1 minute. These makes the power data closer to the actual instantaneous power consumed.

The specific process of adopting the HEDMS is as follows.

*Step 1:* the user sets the operating parameters including rated power, times, comfort settings, etc. According to the equipment functions, the daily powers are simulated based on the established model (if there is no parameter change, the historical data can be directly set as default). Then the total daily power can be obtained by superimposing the equipment powers, and the EC is calculated by combining the electricity price.

*Step 2:* the user can select the equipment that is expected to participate in the HEDMS according to the user preference. The data unit extracts the previous power data in a time step of 1 minute. The GA calculates the operating parameters of the equipment involved in the control, and obtains the power data of the equipment through model simulation.

*Step 3:* Calculate the total daily power and EC after using the control strategy.

### A. OPTIMIZATION MODEL OF HOUSEHOLD EQUIPMENT OPERATING PARAMETERS

The main purpose of the HEDMS in this paper is to reduce the EC based on user comfort. The objective function of the optimization model is to minimize the user daily EC. The constraint is that the finally obtained operating parameters should be within the time range set by the user. At the same time, the indoor temperature should meet the user's settings. The specific mathematical model can be expressed as follows.

The objective function is

$$F_{\text{cost}} = \min \sum_{i=1}^{N} \sum_{j=1}^{M_i} \sum_{t_{\text{final},j}}^{t_{\text{final},j}+t_{dj}} \lambda(t) \times P_i^j(t)/60 \tag{1}$$

The constraints are

$$T_{\text{set,min}} \leq T_{\text{room}} \leq T_{\text{set,max}} \tag{2}$$

$$t_{bj} \leq t_{\text{final},j} \leq t_{ej} \tag{3}$$

### B. OPERATING POWER MODEL OF HOUSEHOLD EQUIPMENT

According to the survey results of household appliances and usage patterns in 12 European countries, the household ownership rate of appliances such as air conditioners, refrigerators, washing machines, dishwashers, televisions, DVDs, and computers is high [15]. In this paper, the models of at least twelve major categories of appliances have been established, covering the overall parameter settings of house such as smart meters, heating equipment, refrigeration equipment, washing equipment, cooking equipment, lighting equipment, computer electronics, batteries and other equipment that can be flexibly converted according to different situations. Refining the large-scale model and building a specific household appliance model, such as a washing machine, dishwasher, dryer and other equipment in the washing equipment; also induction cooker, microwave oven, electric kettle and other equipment in the cooking equipment. This model can meet the needs of most residential users in the daily life.

In the actual operating process of household electrical equipment, most of the operating power is a variable value, which is affected by some factors such as operating mode, surrounding environment and so on. Taking a refrigerator as an example, when the door opens or closes, the temperature change will affect the power. Due to the opening of the door, the refrigerator consumes 0.25 W for each time and this value corresponds to 3.75 W in the daily power [16], [17]. Similarly, the operating power of the washing machine is affected by factors such as water temperature, operating mode, and washing machine efficiency. These factors mainly affect the water heating process which constitutes about 90% of the total power consumption [17], [18]. Therefore, the operating power characteristics of household appliances need to be studied first. Based on the operating power, this paper establishes the equipment mathematical or physical model to express its operating power characteristics. Among them, some typical models are listed.

(1) Overall parameter setting of the house. The physical model is used to build the system architecture of the house. The room exchanges heat with the environment, through exterior walls, roofs and windows [19]. Fig. 1 shows the house parameter setting interface and the model.

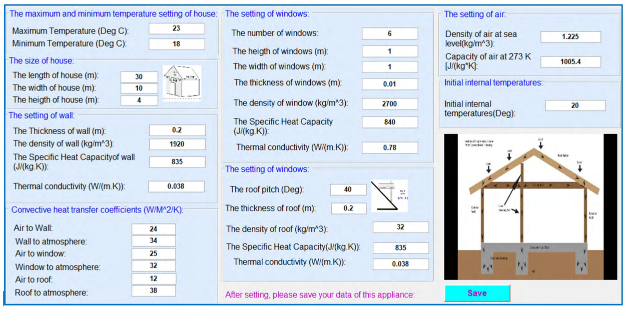
(2) Refrigerator power model. The two-phase fluid cooling model is used to stabilize the temperature within the set range [20]. The motor power in the model is output, considered as the operating power of the refrigerator. The compressor drives the refrigerant through a condenser, an expansion valve, and an evaporator. The controller turns the compressor on and off to maintain the refrigerator compartment temperature within a range around the set temperature. The lower the temperature set in the refrigerator, the faster the temperature rises during the actual operating period, so that the refrigerator needs to be frequently turned on to maintain the temperature. Fig. 2 shows the physical model of the refrigerator.

(3) Air-conditioner model. The relevant cooling parameters generated by the air-conditioner model are employed in the house model to control the temperature of the house.

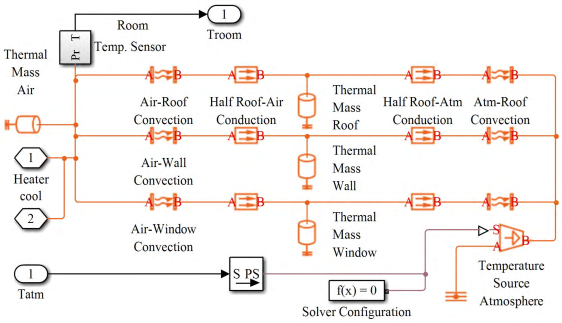
Fig. 3 shows the model of the air-conditioner. The energy-efficiency ratio (EER) of the air-conditioner is an important parameter to measure its performance. It can be expressed as [18]:

$$EER = 3.412\frac{Q_{\text{in}}}{W_{\text{in}}} = 3.412\frac{Q_{\text{in}}}{Q_{\text{out}} - Q_{\text{in}}} \tag{4}$$

(4) Washing machine model. In the parameter setting of the washing machine, refer to [18], give the following variables




(a) The house parameter setting interface




(b) The physical model of the house

**FIGURE 1.** The house parameter setting interface and the model.

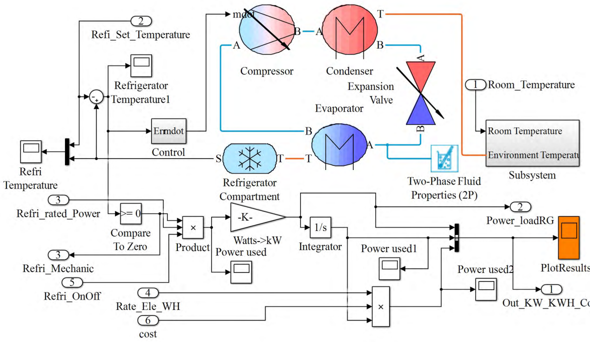



**FIGURE 2.** The physical model of the Refrigerator.

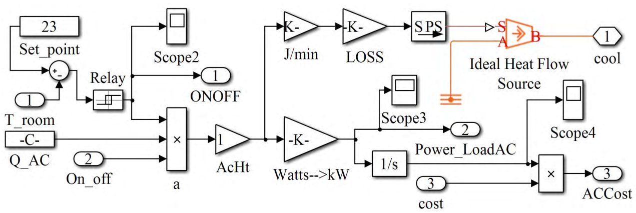



**FIGURE 3.** The model of the air-conditioner.

for the user to set and select: operating mode and the water temperature to simulate the operating power curve better. For the same reason, add similar parameters in the dishwasher.

Fig. 4 and Fig. 5a are schematic diagrams showing the setting interface of the washing machine and the power curve of one washing cycle, respectively. Fig. 5b is a diagram of the

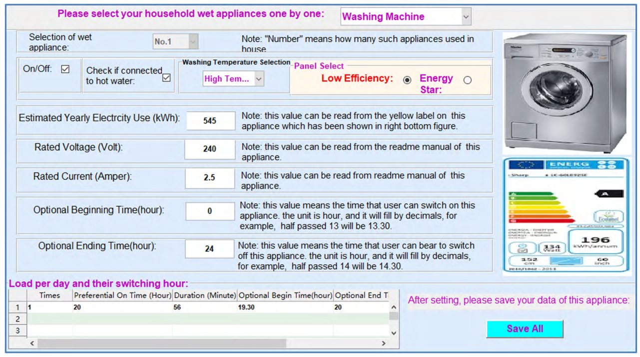



**FIGURE 4.** The setting interface of washing equipment.

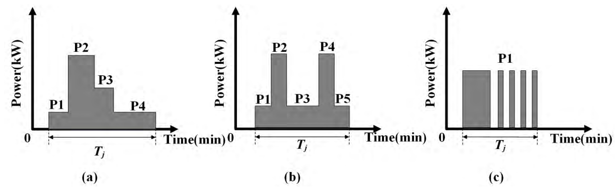



**FIGURE 5.** The power curve of the operation once.

dishwasher. In Fig. 5a, P1 denotes the power corresponding to the filling of water. The washing machine then provides electric heating, increasing its power to P2 for a time period which depends if it is connected to hot water or cold water. After that, washing machine enters the washing mode, which consumes power P3. Finally, the washing machine drains the water, which consumes power P4. For dishwasher, P1 and P5 denote the power corresponding to the filling and draining of rinse water; P2 and P3 correspond to heating water and washing dishes. Unlike a washing machine, the dishwasher needs to dry the dishes after washing, which consumes power P4. The time period of power consumption depends on the efficiency of the machine.

(5) Induction cooker model. The state variable of the cooker is its internal temperature. When the temperature of the cooker reaches on the highest temperature among different levels, the cooker stops working. At this time, the temperature is lowered due to the influence of the ambient temperature. When the temperature reaches the lowest level, the cooker restarts heating. This periodic cycle keeps the internal temperature within the working range and completes the cooking task [21]. Fig. 5c and Fig. 6 are the schematic diagram of operating power and parameter setting interface. The on/off time period of induction cooker can be expressed as (5) and (6).

$$t_{\mathrm{on}} = \frac{1}{C}\left(p_{i,t} - \frac{T}{R}\right) \tag{5}$$

$$t_{\mathrm{off}} = \frac{1}{C} \cdot \frac{T}{R} \tag{6}$$

where $C$ is the specific heat capacity; $T$ is the temperature corresponding to the different levels; $P$ is the power, can be

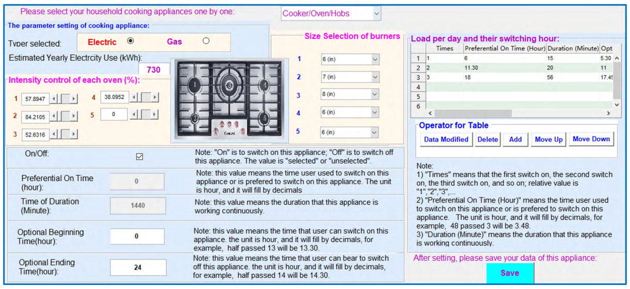



**FIGURE 6.** The setting interface of induction cooker.

set by the intensity percentage; $R$ is the resistance, determined by the area of the induction cooker.

At the same time, through the display interface built in this paper, users can view the power of each equipment. The basic functions of the household appliances have been realized by using the built model, and simulated to obtain data based on the model.

## III. EQUIPMENT PARAMETER OPTIMIZATION BASED ON OPERATING POWER BY GENETIC ALGORITHM

In this section, based on the operating power data, combined with the user's habits, an optimization strategy is given to obtain the operating parameters of the equipment to achieve the lowest daily EC. The pseudo code of the GA based on operating power is shown in Table 1.

### A. HOUSEHOLD EQUIPMENT OPERATION PARAMETER INITIALIZATION

The user sets the basic parameters of the equipment according to the actual situation of the household, such as the number of equipment, power, operating mode, etc. The user also needs to input his own electricity habits parameters. The user's electricity habits are divided into the following parameters: Times, priority opening time (Preferential On Time), working time (Duration), the user's allowable earliest opening time (Optional Begin Time) and latest opening time (Optional End Time).

Since the operating power data of the household electrical equipment is not actually measured, the power data are obtained through model simulation of each household electrical equipment in this paper. Using Matlab's GUI and its inter modulation function with Simulink simulation model, a smart household electricity demand response platform is developed, which realizes the data transfer between the interface and the model. The power curve data of the equipment are obtained by an extraction function with a step size of 1 minute. This program is also suitable for extracting the model simulation data in other platforms, so that the algorithm has certain versatility and portability.

### B. THE GA USED TO OPTIMIZE OPERATING PARAMETERS

The GA is a random search algorithm that draws on the natural selection and genetic mechanism of the biological world [22]. For mixed integer optimization algorithms, when the problems belong to non-convex programming, mixed integer nonlinear programming, the aforementioned optimization methods may not find a feasible solution or the computational expense is too high. Due to the inherited limitation in PSO algorithm, local convergence occurs quite often and global optimized solution cannot be always obtained. The GA is a global optimization algorithm with good search ability, which can quickly search all the solutions in the space, and it does not need many mathematical requirements for the optimization problem solved, whether linear or nonlinear, discrete or continuous objective functions and constraints, the GA can be processed. Therefore, this paper uses the GA to optimize the solution.

The equipment in the HEDMS is divided into the following two categories: transferable loads and non-transferable loads. Non-transferable loads are mainly temperature control devices such as refrigerators, water heaters, and air conditioners. Transferable load means that the working time of the equipment can be changed within a given range, such as washing machine, dishwasher, and induction cooker.

**TABLE 1.** The pseudo code based on operating power.

**Algorithm 1** Genetic algorithm based on operating power

**Input:** $P_i^j(t)$, $t_{dj}$, $t_{pj}$, $t_{bj}$, $t_{ej}$, $\lambda(t)$

**Output:** $t_{\mathrm{final},j}$

**function** " equipment participating in the HEDMS"
  **if** " user selects the equipment to participate in the management strategy" **then** " $P_i^j(t)$ is extracted and stored in 1 min interval, save as $p_{i,t}$ ."
  **end if**
**end function**
**function** "Optimize equipment parameters to obtain $t_{\mathrm{final},j}$ "
  Generate run-time intervals, [ $t_{bj}$ , $t_{ej}$ ], of the equipment which is chosen to participate in the control
  Input the relevant parameters of the genetic algorithm including the number of iterations, the individual number in the population, the method of individual selection, the way of chromosome intersection and variation
  $\lambda(t)$ expanded in mins
  Population binary coding and initialization
  Calculate $F_{\mathrm{cost}}$
  Fitness value calculation
  **while** "not satisfy the terminate condition " **do**
  {
  Individual choice
  Chromosomal intersection
  Chromosomal variation
  Generating new population
  Calculate the power $P$ in the new population
  Calculate $F_{\mathrm{cost}}$
  Calculate the individual fitness value of new population
  Sorting the fitness values, eliminating individuals with small fitness values, and maintaining the constant number of individuals in the new population
  }
  **end while**
  Generate the final population
  Select the individual with the highest fitness value
  Binary decode the individual, output $t_{\mathrm{final},j}$
**end function**

**TABLE 2.** Some household equipment parameters (Unit: Min).

| Equipment | $t_{pj}$ | $t_{bj}$ | $t_{ej}$ | $\left[t_{bj}, t_{ej}\right]$ | $t_{dj}$ |
|---|---|---|---|---|---|
| Washer | 1200 | 420 | 1260 | [420, 1260] | 56 |
| Dishwasher | 1170 | 1170 | 1230 | [1170,1230] | 60 |
| PC 1 | 480 | 420 | 1080 | [420,1080] | 346 |
| PC 2 | 1320 | 1260 | 1380 | [1260,1380] | 15 |
| Laptop | 720 | 660 | 762 | [660,762] | 678 |
| Microwave1 | 360 | 320 | 360 | [320,360] | 5 |
| Microwave2 | 690 | 680 | 705 | [680,705] | 4 |
| Microwave3 | 1080 | 1070 | 1110 | [1070,1110] | 10 |
| Game machine | 1320 | 1130 | 1373 | [1130,1373] | 67 |
| DVD | 1260 | 1020 | 1315 | [1020,1315] | 125 |
| Kettle | 1080 | 1070 | 1110 | [1070,1110] | 10 |

The HEDMS in this paper is used for mainly the scheduling of transferable load and processing the operating power data. Control of overall participating household electrical equipment is represented by a set $A$,

$$A = \{1, 2, \ldots, i, \ldots, N\}$$

For any equipment $i$ that belongs to $A$, the power data can be represented by $P_i$. In actual situations, the time interval for operating power data varies which results in the inability to extract data at a specific moment. For example, during the sampling process, the operating power data of 8:59:59 and 9:00:02 can be obtained, but the data of 9:00:00 is skipped. This paper uses interpolation method to process power data. Select the power value of the two nearest points before and after the sampling point to average, as the power of the sampling point.

The processing operating power data are:

$$P_i = [p_{i,1}, p_{i,2}, \ldots, p_{i,1440}]$$

According to the above analysis, the total daily power data of the set $A$ of the household equipment participating in the control are

$$P = [P_1, P_2, \ldots, P_{1440}]$$

where $P_t = \sum_{i\in A} p_{i,t}$, $t = 1, 2, \ldots, 1440$.

The operating parameters of some household equipment are shown in Table 2. Different users may have quite different daily usage habit of the equipment. These parameters can be modified according to the actual situation. This paper takes a family in a Chinese city as an example. The operating power of PC, microwave ovens, DVDs and kettles is basically the same as the rated power, and can also be calculated by collecting the operational data through actual operation. In this paper, the calculation and analysis of these equipment are performed with the rated power. The preferential opening time of the equipment is assumed according to the daily usage habit of the user, indicating the time interval allowed by the user. The allowable time period is an important parameter for measuring the comfort of the user. It is the first guarantee for user comfort, that is, scheduling within a time range the user accepts. If the equipment scheduling result $T_{\text{final},j}$ is obtained by the optimization algorithm, the closer to $T_{pj}$ it is, the better. That is to say, the algorithm obtains an optimal on-time $T_{\text{final},j}$ within the allowable time period, so that the electric equipment has the lowest cost after completing the task.

This paper also designs a selection interface that is expected to participate in the HEDMS. The interface reads all the information of the household equipment, and the user can select the desired control according to his or her preference and actual situation. This is second guarantee for user comfort. At the same time, by selecting, some equipment that do not participate in the control, these equipment can be excluded in the GA calculation, which improves the calculation speed of the algorithm.

Assume that the initial population has 300 individuals, each of which contains the start time of all selected electrical equipment, the opening time of each equipment participating in the control as the individual chromosome, and each row represents an individual in the population. Each column corresponds to the actual opening time of each household appliance, and each opening time meets the limitation of the opening time range.

After the initial population of the equipment opening time is generated, the time is chromosomally encoded. Since $2^{11} > 1440 > 2^{10} 2^{10}$, the length of the chromosome is selected to be 11 bits to accurately and completely indicate the time of each equipment.

The size of the individual fitness value in the GA reflects the degree of individual's pros and cons in the population. The greater the fitness value is, the higher the survival rate of the individual in the population. There are also differences in the criteria for judging fitness based on the objective function. To this end, the objective function of the GA is:

$$F_{\text{cost}} = \min \sum_{t=1}^{1440} \lambda(t) P_t / 60 \tag{7}$$

According to the objective function, the ultimate goal of the problem is to solve the minimum value and define the fitness value. In this paper, the daily EC of different individuals is compared with the individual's maximum EC, and then the final result is subtracted from 1 to achieve normalization and fitness distribution. The fitness value is:

$$\text{fitness} = 1 - F_{\text{cost}} / \max(F_{\text{cost}}) \tag{8}$$

By appropriate selection methods, chromosome crossing and variation methods and screening of new populations, according to the number of iterations, selection, crossover, mutation, screening and judgment are gradually carried out, and finally the best gene population is obtained. The optimal individual data of the population is selected and output, as the actual opening time of each equipment participating in the control.

### C. OPTIMIZATION ALGORITHM VERIFICATION

The design principle of the loop optimization search algorithm is the stepwise iterative calculation.

$$F_{\cos t} = \min \sum_{i=1}^{N} \sum_{j=1}^{M_i} \int_{T_{bj}}^{T_{ej}+T_{dj}} \lambda(t) \times P_i^j(t)/60\mathrm{d}t \quad (9)$$

The user inputs the operating time and parameters of various appliances during the initial setting, and obtains a series of power data after the simulation. The power data and the electricity price curve are iterated in the time period when the user sets the earliest and the latest allowable time. By calculating and selecting the lowest EC of the equipment as the result, with output, opening time and operating time of the equipment at this time. Each type of appliance involved in the control performs a loop search of the algorithm, finally obtains the opening time and operating time of all electrical appliances, and calculates the total daily EC. The calculation formula of the loop algorithm is expressed as (7).

## IV. CASE VERIFICATION

This section will analyze the effect of adopting a HEDMS for single equipment and all household appliances by taking typical cases. In the case of single equipment, the parameters obtained by the loop algorithm are taken as a reference, and the optimization parameters of the GA based on the operating power are compared with the parameters obtained by the GA based on the rated power to verify that the algorithm can realize the power load transfer and have higher accuracy. At the same time, comparing the algorithm optimization time of single equipment with the algorithm optimization time of all equipment shows that setting the equipment control interface can effectively improve the running speed. In the case of all appliances, by selecting all equipment for control, the power curves before and after the strategy are obtained, the daily EC is calculated, also the algorithm can effectively reduce the EC and realize the power load transfer, as well as reduce the PAR.

### A. GA PARAMETERS AND ELECTRICITY PRICE INFORMATION

The GA used in this paper is as follows: the generation gap is 1.2; the individual selection method is the roulette selection based on the fitness of the individual; the chromosome intersection method is the two-point intersection method, the probability is 0.95; the chromosome variation method is the basic position variation, the probability is 0.025.The number of individual and iterations are 300 and 200. The RTP data information $\lambda(t)$ (unit: \$/kWh) are {0.02411, 0.02165, 0.02059, 0.02039, 0.02079, 0.02228, 0.0270, 0.03138, 0.02938, 0.03219, 0.03374, 0.03655, 0.03683, 0.04087, 0.04316, 0.04629, 0.04913, 0.04839, 0.04248, 0.04949, 0.04504, 0.03721, 0.03032, 0.02591} [23]. The data come from RTP information published by the US Ameren Power Company website. Fig. 7 shows the RTP of Illinois on October 1, 2018.

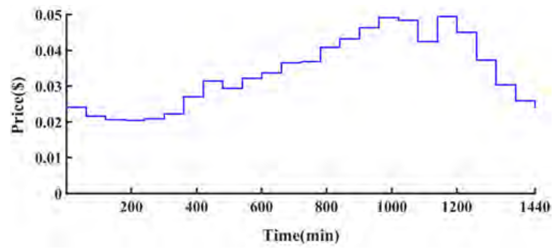



**FIGURE 7.** The RTP of Illinois on October 1, 2018.

**TABLE 3.** Equipment initialization example.

| Individual | Opening time of each electrical equipment (min) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | 1199 | 1319 | 268 | 325 | 687 | 1087 | 673 | 420 |
| 2 | 1185 | 1319 | 137 | 336 | 687 | 1098 | 676 | 421 |
| 3 | 1198 | 1318 | 266 | 320 | 690 | 1097 | 675 | 420 |
| 4 | 1186 | 1319 | 11 | 336 | 682 | 1108 | 670 | 420 |
| 5 | 1193 | 1315 | 14 | 325 | 686 | 1089 | 669 | 420 |

The household equipment participating in the control selection interface is shown in Fig. 8, the intelligent platform provides the user with an interface for the equipment participation management strategy, and the user can select according to his actual situation, thereby enhancing the degree of user participation. The initiating of response gives the user autonomous choice, and can avoid the calculation of the equipment that does not participate in the HEDMS, reduce the amount of calculations, and improve the operation speed.

### B. SCHEDULING RESULTS FOR SINGLE EQUIPMENT

When the user only selects single equipment to participate in the HEDMS, the strategy proposed in this paper improves in running speed and calculation accuracy. Taking the optimization of the operating parameters of the induction cooker as an example, the results obtained by the GA based on the operating power are compared with the results of the loop algorithm to verify the correctness of the algorithm, and the comparison with the results based on the rated power proves that it can effectively improve the calculation accuracy. In addition, calculate the running time of the algorithm to verify the improvement in speed.

The parameter setting interface of the induction cooker is shown in Fig. 5. The user can set the power, use time, the earliest and latest time by the actual situation and daily habits. The optimization calculation is performed after the setting. The optimized operation parameters are shown in Table 4.

In Table 4, $t_{\mathrm{final},1}$ is the opening time obtained by the loop search algorithm; $t_{\mathrm{final},2}$ is the opening time obtained by the GA at rated power; $t_{\mathrm{final},3}$ is the opening time obtained by the GA at operating power.

The daily power curve of the induction cooker before and after the HEDMS is shown in Figure 9. Combined with Table 3, it can be found that the opening time of the induction cooker in the morning, noon and night are optimized from

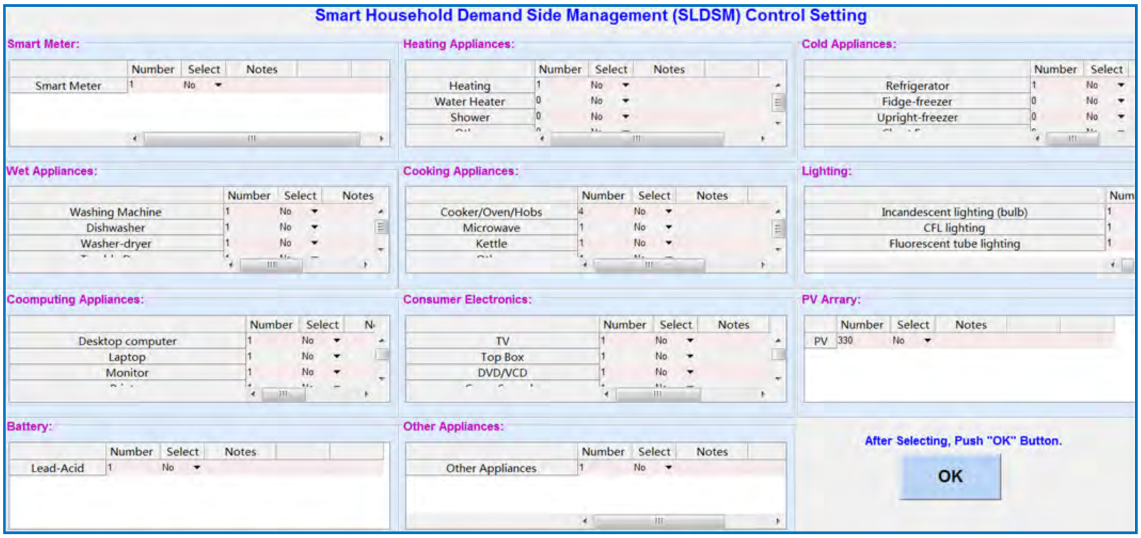



**FIGURE 8.** The equipment control selection interface.

**TABLE 4.** Cooker before and after using the strategy.

| Time(min) | $t_{pj}$ | $t_{dj}$ | $t_{bj}$ | $t_{ej}$ | $t_{\text{final},1}$ | $t_{\text{final},2}$ | $t_{\text{final},3}$ |
|---|---|---|---|---|---|---|---|
| morning | 360 | 15 | 330 | 390 | 340 | 330 | 339 |
| noon | 690 | 20 | 660 | 720 | 690 | 665 | 692 |
| night | 1080 | 56 | 1065 | 1140 | 1135 | 1140 | 1137 |

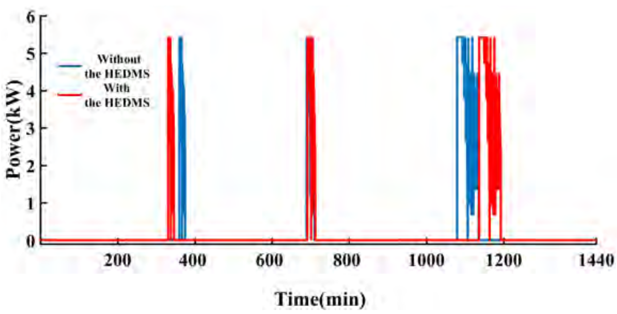



**FIGURE 9.** The daily power curve of the induction cooker equipment before and after using the strategy.

6:00, 11:30 and 18:00 to 5:39, 11:32 and 18:57. In this paper, the algorithm with the lowest EC as the objective function can effectively optimize the operating parameters.

From the power curve comparison of the cooker before and after adopting the HEDMS, it can be deduced that: (1) The results obtained by the GA based on the operating power data and the loop algorithm are similar, and are better than the results based on the rated power data. It shows that the GA can effectively manage the equipment participating in the strategy, realize load transfer, and reduce EC. (2) The running time of the strategy is also calculated in this paper. Compared with the calculation based on the overall calculation and the distribution according to the results, this paper only optimizes the selected equipment. The results show that the time required for all equipment to be calculated is 85.60 s, the time required to calculate only the cooker is 13.20 s. The strategy can effectively improve the running speed.

**TABLE 5.** Household electricity cost comparison.

| Household | Cost before controlled ( \$ ) | Cost using the cyclic search strategy ( \$ ) | Cost using the GA strategy ( \$ ) |
|---|---|---|---|
| 1 | 1.35007 | 0.98297 | 0.99028 |
| 2 | 1.43881 | 1.0261 | 1.05902 |
| 3 | 1.53502 | 0.9889 | 1.02195 |

### C. SCHEDULING RESULTS OF OVERALL HOUSEHOLD APPLIANCES

The following is a comparison of daily EC before and after using the three households participate in the HEDMS, as shown in Table 5. The power setting of household appliances is outlined in [24] regarding the power consumption of most common appliances. Table 5 provides data on the EC without the management strategy, the EC using the loop algorithm strategy, and the EC using the GA strategy. It can be seen that the EC using the two algorithms is significantly reduced compared to the EC without the control strategy, and can be used to manage the household equipment to reduce the EC.

The total EC of the household appliance that the user selects to adopt the HEDMS changes with the number of iterations is shown in Fig. 10. A power curve diagram before and after the strategy is shown in Fig. 11. Combining with Table 5, it can be seen that:

(1) By adopting the strategy, some of the equipment during the peak hours of power consumption will be deferred, that is, the effect of weakening the peak can be achieved by load transfer. When the strategy is not adopted, the peak value is 13.0 kW, and PAR is 8.75. After adopting the strategy, the peak value is 8.29 kW, the PAR is 5.58, and the PAR is reduced by 36.2%, which indicates that the HEDMS can

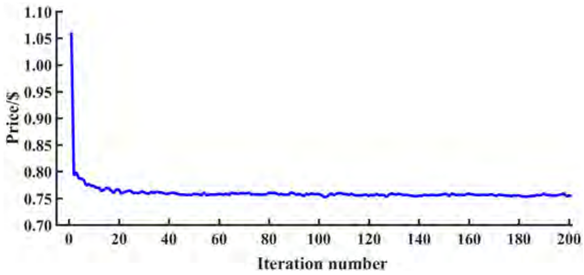



**FIGURE 10.** **The cost of the appliance that the user selects to adopt the strategy changes with the number of iterations.**

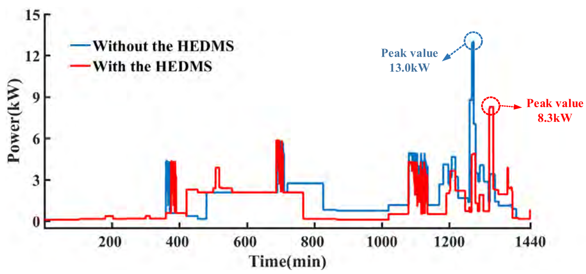



**FIGURE 11.** **The power curve diagram before and after the GA control strategy.**

effectively reduce the PAR, making the power curve more stable. It plays an important role in improving the stability of the power-supply network.

(2) In the three households, after adopting the HEDMS, the EC was reduced from 1.35 dollars to 0.99 dollars; 1.44 dollars to 1.06 dollars; 1.54 dollars to 1.02 dollars, the percentage reduction was 26.7%, 26.4% and 33.8%. It shows that the GA can effectively reduce the daily EC, and the loop algorithm is used to verify that GA can reduce the EC and maximize the user's comfort.

## V. CONCLUSION

This paper presents a household energy demand management strategy based on the operating power by genetic algorithms, aiming to minimize daily electricity cost on the prerequisite of guaranteed user-comfort. Through typical case verifications by simulations, the following conclusions can be obtained:

(1) The household energy demand management strategy proposed in this paper can effectively reduce the daily electricity cost. The average daily electricity cost of the user is reduced by 29.0%. Compared with the algorithm based on the rated power, the results are more accurate. The household energy demand management strategy can also improve the running speed and allow the user to choose. In addition, after applying the household energy demand management strategy, the peak-to-average ratio is reduced by 36.2%. It is a win-win strategy for users and sales companies.

(2) The household energy demand management strategy proposed in this paper can incorporate comfort values into the optimization calculation to meet higher demand, if there is a standard for comfort value calculation. The users can assign the weight of comfort value and daily electricity cost in the fitness value calculation to meet their needs. This shows that the genetic algorithms can meet more requirements when scheduling electrical equipment, which is not available in the loop algorithm.

(3) The household energy demand management strategy proposed in this paper can set the power threshold to avoid the power surge caused by the concentration of the power equipment in a certain period of time. The genetic algorithm analyzes the power curve from a global perspective. In the future research, if the smart grid requires the user to have a power value that cannot be higher than the household power threshold at some time, the loop algorithm cannot satisfy this requirement because of its simple step-by-step iteration, which is easy to make the equipment run in a centralized time period, resulting in a high peak. The household energy demand management strategy can meet the higher requirements of smart control by setting the power threshold as a constraint and applying the constraint as a penalty function in the genetic algorithm.

(4) The accuracy of the household energy demand management strategy proposed in this paper will be greatly improved, when the operating power data of each user's electrical equipment is collected. Data closer to the actual situation makes the strategy practical. This paper does not currently study the impact of distributed energy, price incentives and other factors on demand response plans. In the future work, these factors will be analyzed and discussed. In addition, the management and scheduling of household electrical equipment will be more comprehensively realized.

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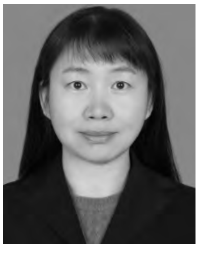

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