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Multi-objective Optimal Control of Smart Home Loads Based on Internet of Things

Ke-Ling Bi[1,*], Isabel Reyes[2]

[1]School of Information Engineering, Liaodong University, Dandong 118003, P. R. China
wenya_wu1114@163.com

[2]College of Information Science, Adamson University, Ermita, 1000 Metro Manila, Philippines
fd0259@163.com

*Corresponding author: Ke-Ling Bi

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Abstract. *Traditional load control methods for smart homes usually focus on the optimisation of a single objective, making it difficult to take into account both electricity cost and user comfort. In addition, these methods suffer from certain delays and computational bottlenecks when dealing with real-time data and large-scale data, which limit their effectiveness in practical applications. In order to solve these problems, this study proposes a multi-objective optimal control method for smart home loads based on the Internet of Things (IoT). Firstly, through IoT technology, the system is able to monitor and collect home environmental parameters (such as temperature, humidity and light intensity) and electricity consumption data in real time, and upload them to the cloud platform for processing and analysis, which ensures the continuity and real-time data collection. Secondly, the Marine Predator Algorithm (MPA) is used for multi-objective optimisation, which achieves comprehensive optimal control of electricity price and user comfort by simulating the foraging behaviour of marine predators. The experimental results show that compared with the traditional algorithm, the MPA has significant advantages in global search capability and convergence speed, and can more effectively reduce the cost of electricity and improve user comfort. Under the same conditions, the MPA algorithm reduces the average electricity load from 3.57 kW to 2.79 kW and improves the user comfort index from 3.1 to 11.3, respectively, which reduces the cost of electricity by 21.9% and significantly improves the user experience. The system enables users to access and control smart home devices in real time, enabling efficient management and optimisation of home energy.*
Keywords: smart home; internet of things; multi-objective optimisation; marine predator algorithm; load control

1. **Introduction.** As an important part of modern family life, smart home has great research value and necessity. Through smart home technology, automated control of home appliances and equipment, energy management and security monitoring can be realised, thus improving the convenience and comfort of life [1, 2]. Meanwhile, with the increasing concern for energy conservation, environmental protection and sustainable development, the application of smart home systems in energy optimisation and management is particularly important. Smart home can not only effectively reduce home energy consumption [3], but also optimise the efficiency of energy use [4] and reduce carbon emissions [5] through data analysis and intelligent control technology, which has important social and economic benefits.

The application of Internet of Things (IoT) and group intelligence algorithms in smart home load control has great potential. IoT technology interconnects all devices in a smart home through a variety of sensors and communication devices to achieve real-time data collection, transmission, and processing so as to achieve comprehensive sensing and control of the home environment [6, 7]. Group intelligence algorithms, such as the Grey Wolf Optimization (GWO) algorithm [8], Particle Swarm Optimization (PSO) algorithm [9], and Marine Predator Algorithm (MPA) [10, 11], are able to efficiently solve complex multi-objective optimisation problems by simulating the behaviour of groups of people in nature. The application of these algorithms in smart home load control can achieve the dual optimisation of energy consumption and user comfort, and enhance the overall performance of smart home systems.

The research objective of this paper is to propose a multi-objective optimal control method for smart home loads based on the Internet of Things and group intelligence algorithms. By designing a reasonable tariff model and comfort model, constructing a multi-objective optimal control framework and solving it with MPA, the optimal control of smart home load is finally achieved. In the experimental part, the effectiveness and superiority of the proposed method are verified through simulation experiments, and the results are analysed to provide a reference for the future development of smart home systems.

1.1. **Related work.** In the traditional method of electrical equipment load control, a centralised control architecture is usually used. The dispatch centre manages the operation of electrical equipment by sending control information to ensure the stability of the power system. However, this approach has many problems when dealing with large-scale power networks. Ruiz et al. [12] pointed out that the centralised control architecture is prone to the problems of system overload and long response time when dealing with large-scale load control. In addition, centralised control requires a large infrastructure and high maintenance costs, which is a major limitation in practical applications.

In order to overcome the disadvantages of centralised control, researchers have proposed distributed control architecture. Distributed control architecture enables remote control of different devices over a network and overcomes the limitation of geographical location. Devlin et al. [13] proposed a method for home load monitoring using smart meters. Although smart meters can effectively monitor the electricity consumption of a home, they can only achieve simple on-off control, which is unable to meet the demand for complex load optimisation. Çimen et al. [14] designed an embedded controller to achieve load control by modifying existing equipment, but this method requires significant modification of the original equipment and is less practical.

In the current research on smart home load control, the application of Internet of Things (IoT) technology has become a research hotspot. IoT technology achieves comprehensive sensing and control of the smart home environment through various sensors and communication devices. The IoT-based smart home system optimises power usage by monitoring environmental parameters in real time. In addition, the rise of multi-objective load control technology has brought new development opportunities for traditional load control methods. Most multi-objective load control achieves optimal power system operation by regulating load response time and power. Soares et al. [15] proposed a multi-timescale multi-objective load scheduling strategy that improves the stability of the grid by modelling the uncertainty of power generation. However, the multi-objective load control needs to consider the equipment usage habits and user comfort when it is implemented, which puts higher requirements on the design of the algorithm.

Population intelligence algorithms, such as Grey Wolf Optimization (GWO), PSO, and Differential Evolution (DE) [16], have shown promising applications in smart home load control. Arabali et al. [17] proposed a Genetic Algorithm (GA)-based load optimisation approach to optimise load allocation by simulating biological evolutionary processes. However, the genetic algorithm suffers from slow convergence and tendency to fall into local optimal solutions when facing high and multi-peak optimisation problems. Izawa and Fripp [18] performed multi-objective optimal control of air-conditioning systems by PSO, and although they achieved some results in optimising tariffs and customer comfort, the algorithm suffers from some delays in processing real-time tariff signals and still needs to be improved in terms of solution accuracy and stability. In addition, Alturki et al. [19] investigated the demand-side load response mechanism based on the GWO algorithm, which minimises the cost of electricity consumption by optimising the balance between electricity supply and demand. However, the method fails to fully consider the user's habits and comfort level, resulting in certain limitations in practical applications.

1.2. **Motivation and contribution.** Traditional smart home load control methods usually have difficulty in optimising both electricity costs and user comfort. These methods often focus on single-objective optimisation, ignoring the actual usage habits and comfort needs of users, leading to greater limitations in practical applications. In addition, existing methods have high computational complexity when dealing with multi-objective optimisation problems, and there are certain delays and bottlenecks when facing large-scale and real-time data. These problems make it difficult for existing load control methods to be widely applied in smart home systems. In order to overcome the above problems, this paper proposes a multi-objective smart home load optimisation control method based on MPA. MPA is able to solve the multi-objective optimisation problem efficiently by simulating the foraging behaviour of marine predators and performs well in terms of global search capability and convergence speed. The main innovations and contributions of this study include:

(1) Aiming at the problem that existing load control methods fail to fully consider user comfort, the multi-objective optimal control framework proposed in this paper comprehensively optimises the cost of electricity consumption and user comfort by designing a reasonable comfort model combined with an electricity price model. The framework is able to achieve the efficient use of power resources while guaranteeing the comfort experience of users.

(2) In order to solve the problem of high computational complexity of the existing algorithms in dealing with multi-objective optimisation problems, MPA is introduced in this paper. MPA has a powerful global search capability and fast convergence characteristics, and by simulating the behaviour of the marine predator in different feeding stages, it can solve the multi-objective optimisation problems efficiently and significantly reduce the computational complexity.

(3) Aiming at the bottleneck problem of real-time data and large-scale data processing, the optimal control method proposed in this paper combines the Internet of Things technology and cloud platform to monitor and process the data of smart home devices in real time. By dynamically adjusting the parameters of the tariff and comfort model, it achieves real-time optimal control of smart home loads, enhances the system's response speed and processing capability, and adapts to large-scale application environments.

2. Smart home cloud platform control system.

2.1. **System framework.** The system block diagram of the smart home cloud platform control system is shown in Figure 1, which mainly includes the following modules:

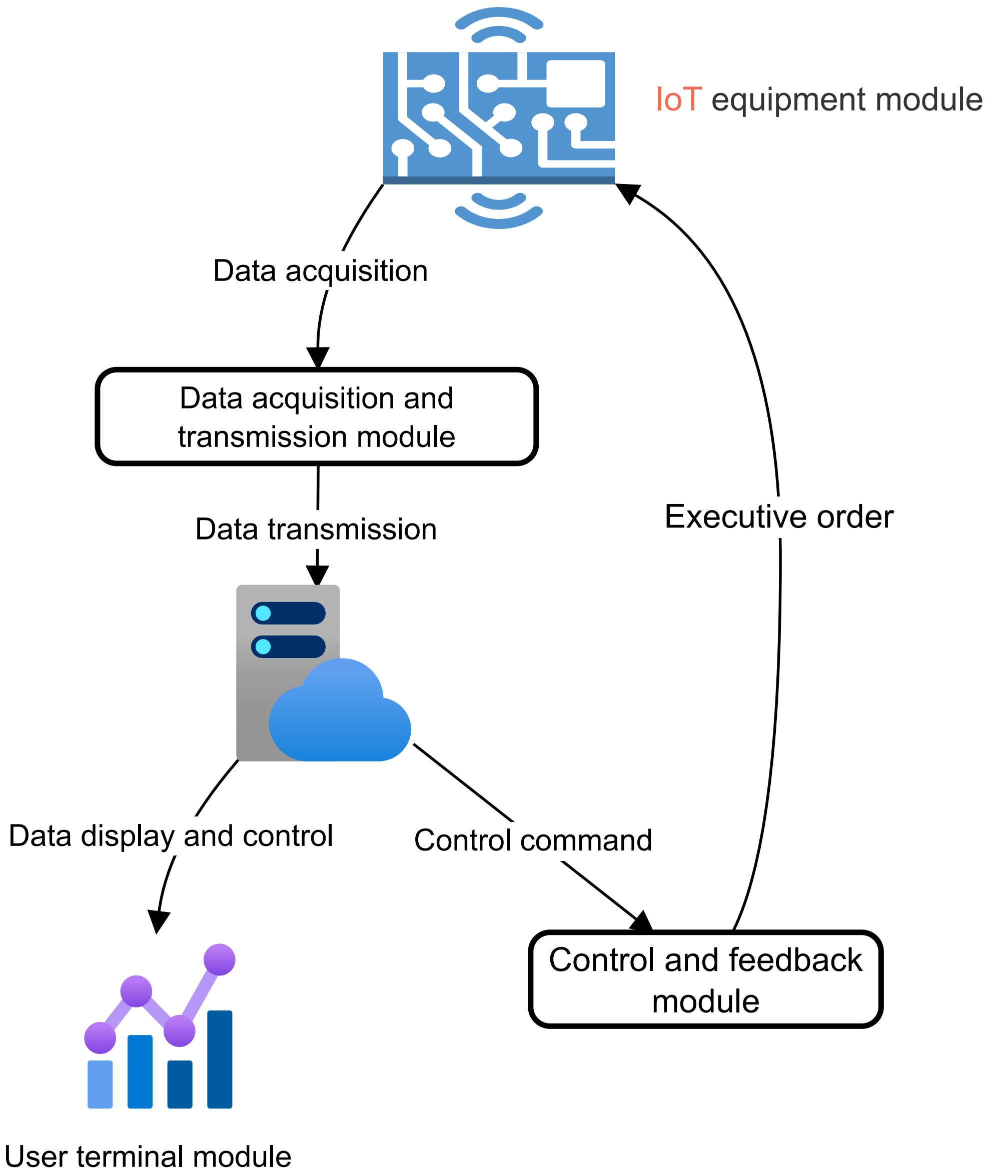

Figure 1. System Block Diagram of Smart Home Cloud Platform Control System

(1) **IoT device module:** this module includes various smart home devices, such as smart lights, temperature and humidity sensors, air quality sensors, and smart sockets [20, 21]. These devices are connected to the data acquisition and transmission module through wireless communication modules (e.g., WiFi, ZigBee, etc.). The smart light in the IoT device module is connected via a WiFi module to remotely control the switch and brightness. The temperature and humidity sensor monitors the environmental temperature and humidity data in real time and uploads it to the cloud platform via the WiFi module. The air quality sensor detects indoor air quality and the data is also uploaded through the WiFi module. Smart socket controls the switching status of home appliances and monitors power usage.

(2) **Data Acquisition and Transmission Module:** this module is responsible for acquiring data from IoT devices and transmitting the data to the cloud platform server via a wireless communication module. Commonly used communication protocols include MQTT, HTTP, etc. The ESP8266 WiFi module is used for data transmission between devices and supports the efficient MQTT protocol [22]. The data processing unit performs

preliminary processing and filtering of sensor data to ensure the accuracy of the uploaded data.

(3) **Cloud platform server:** the cloud platform server is the core of the whole system, responsible for data storage, processing and analysis. The server receives data from IoT devices, processes and analyses them, and transmits the results to the user terminal. A distributed database is used to store a large amount of sensor data [23]. Big data analysis technology is used to analyse household electricity and environmental data and provide optimisation suggestions. Based on the analysis results, control commands are generated and sent to IoT devices.

(4) **User Terminal Module:** User terminals include smartphones, tablet PCs, etc., which interact with the cloud platform server through application programmes (APP) or web interfaces. Users can monitor the status of smart home devices in real time through the terminal and perform control operations. Users can view real-time data, set control strategies, and receive alarm notifications through the APP. Provide an intuitive dashboard to show the overall power consumption and environmental conditions of the home.

(5) **Control and Feedback Module:** This module sends control commands to the IoT device according to the user's operation or preset control strategy to achieve remote control of the device. At the same time, the status information of the device is fed back to the user terminal in real time. Execute the operation of the device through the control commands sent by the cloud platform server. Real-time monitoring of equipment status and feedback to the user terminal ensure the accuracy and timeliness of operation.

2.2. **IoT device selection.** In order to achieve multi-objective optimal control of smart home loads, the following IoT devices are selected in this study, which have a good overall performance in terms of functionality, performance and cost.

(1) **Temperature and humidity sensor**: In this study, DHT22 temperature and humidity sensor was selected [24], which has high accuracy and stability. DHT22 is capable of real-time monitoring of indoor temperature and humidity and outputting them through digital signals, which is suitable for various environmental monitoring applications.

(2) **Air quality sensors**: The MQ-135 air quality sensor [25] was selected for detecting the concentration of harmful gases in indoor air, such as NH_3, NO_x, alcohol, benzene, smoke, and CO_2. With its high sensitivity and fast response characteristics, the MQ-135 is ideally suited for use in air quality monitoring in smart homes.

(3) **Smart Socket**: The smart socket is a Sonoff S26 WiFi smart socket [26], which supports remote control and power monitoring, allowing users to remotely control the on/off status of their home appliances and view real-time power usage through a mobile app.

(4) **Intelligent Lighting**: Choose the Philips Hue smart bulb, which supports multiple colour adjustments and remote control via a mobile app or voice assistant.

(5) **WiFi module**: The ESP8266 WiFi module is used, which is small in size, low in power consumption, and supports a variety of network protocols, making it suitable for integration in a variety of IoT devices to achieve wireless transmission of data.

(6) **Microcontrollers**: STM32F103C8T6 microcontroller is selected as the core control unit, which has high performance and low power consumption characteristics and is suitable for complex embedded system design.

The selection of smart home devices is shown in Table 1. By selecting the above devices, a smart home system with perfect functions and reliable performance is constructed, which can realise real-time monitoring and optimal control of home electricity equipment, and provide users with an intelligent, efficient and convenient home experience.

Table 1. Smart Home Device Selection

No.	Equipment name	Model number	Main parameters
1	Temperature and humidity sensors	DHT22	Temperature range: −40°C to 80°C, humidity range: 0-100% RH, response time: <5 seconds
2	Air quality sensors	MQ-135	Measuring range: 10-1000ppm, response time: <10 seconds
3	Smart socket	Sonoff S26	Rated Voltage: 100-240VAC, wireless Standard: WiFi 2.4GHz 802.11b/g/n
4	Intelligent lighting	Philips Hue	Power: 9.5W, lifespan: 25000 hours, wireless standard: Zigbee
5	WiFi module	ESP8266	Operating voltage: 3.3V, wireless standard: IEEE802.11b/g/n, support protocols: TCP/IP UDP HTTP MQTT, etc.
6	One-chip computer	STM32F103C8T6	Core: ARM Cortex-M3, main frequency: 72MHz, Flash: 64KB, I/O pins: 37 GPIO pins

2.3. **Cloud platform server.** To ensure the efficiency and reliability of the system, this study chooses a powerful cloud server and combines it with advanced data processing technology to construct a safe, efficient and scalable smart home cloud platform.

The architecture of the cloud platform server is designed to target high availability, scalability and security. The server adopts distributed architecture and supports multi-node deployment, which can handle a large number of concurrent requests and ensure stable system operation. Through load balancing technology, the server is able to distribute requests evenly among multiple nodes, preventing single point of failure and improving the reliability of the system.

The cloud platform server receives data from IoT devices and processes and analyses it in real time. The data processing module uses big data processing technology to quickly process massive data and extract useful information. The processed data is stored in a distributed database to ensure data security and scalability. The server supports a variety of database types, including relational databases and non-relational databases, and can flexibly respond to different data storage needs.

In the cloud platform server, the setting of data points is crucial, which is directly related to the data collection, processing and display effect. According to the requirements of the smart home system, several key data points are set as shown in Table 2.

Table 2. Key Data Point Settings in Smart Home Systems

Data point name	Data type	Unit of measure	Read and write properties	Resolution	Minimum	Maximum
Temperature	Numeric	°C	Read-only	1	-40	80
Humidity	Numeric	%RH	Read-only	1	0	100
Air Quality	Numeric	—	Read-only	1	0	500
Lightt	Boolean	—	Writable	—	—	—
Plug	Boolean	—	Writable	—	—	—

3. Multi-objective modelling of smart home loads.

3.1. **Three-level tariff model.** With the development of smart grid, load control through effective tariff models has become a research hotspot. Reasonable tariff models can not only help managers to reduce peak power consumption, improve load factor, and save power costs, but also help users to save electricity costs.

In the smart home system, in order to achieve multi-objective optimal control of loads, it is crucial to design a reasonable electricity price model. The Three-Tier Electricity Price Model (TEPM) aims to balance the electricity supply and demand by dynamically adjusting the electricity price to reduce the cost of electricity consumption, while improving the efficiency of electricity consumption by users. The model is divided into peak, off-peak and silent hours, each with a different price to incentivise consumers to use electricity during off-peak hours to optimise grid load.

Peak Period is usually when the demand for electricity is highest, such as during daytime working hours. Tariffs are higher during this time in order to reduce the amount of electricity used at this time to relieve pressure on the grid. Off-Peak Period is when demand for electricity is low, such as at night. The lower price of electricity during this period encourages users to move some non-urgent demand to this period, thus increasing the utilisation of electricity resources. Silent Period is when the grid is least loaded, such as late at night. Electricity prices are lowest during this period to maximise the use of idle power resources.

In order to effectively control smart home loads in practice, this paper designs a three-tier tariff model at hourly level to separately price the above three time periods in a hierarchical manner, which is modelled as follows:

$$O(C_h) = \begin{cases} \alpha_h \cdot C_h, & \text{if } 0 \leq C_h \leq \delta_1 \\ \beta_h \cdot (C_h - \delta_1) + O(\delta_1), & \text{if } \delta_1 < C_h \leq \delta_2 \\ \gamma_h \cdot (C_h - \delta_2) + O(\delta_2), & \text{if } C_h > \delta_2 \end{cases} \tag{1}$$

where $O(C_h)$ is the pricing function for time period h; C_h is the total electricity consumption of the user in time period h; α_h, β_h and γ_h are the prices of electricity consumption in peak, low peak and silent time periods, respectively; δ_1 and δ_2 are the tariff grading thresholds.

The details of $O(C_h)$ are calculated as follows:

$$C_h = \sum_{i=1}^{n} d_{h,i} \tag{2}$$

where n denotes the number of electricity consuming devices owned by the user, and $d_{h,i}$ denotes the electricity consumption of the i-th device in time period h.

Since the system is adjusted in real time according to the equipment power consumption, the tiered tariff will have some error when switching. For this reason, the following error model is designed:

$$C_{h'} = \sum_{i=1}^{n} \lambda_{h,i} \cdot d_{h,i} \tag{3}$$

where $\lambda_{h,i}$ is the delay factor for each device at time slot h and $\lambda \geq 0$.

In practical application, the smart home system monitors electricity usage in real time through IoT devices, and dynamically adjusts the electricity price for each time period by combining the data processing capability of the cloud platform. The system automatically recommends the best time slots for electricity use based on the user's electricity use behaviour and preferences, helping the user to reduce the cost of electricity use while improving the efficiency of electricity use.

For example, when a user uses a large amount of electricity during peak hours, the system will remind the user to use power-intensive equipment, such as washing machines and dishwashers, during low-peak or silent hours, thus reducing the amount of electricity used during peak hours and lowering the electricity bill.

In summary, the complete tariff model is shown as follow:

$$E = \sum_{h=1}^{H} \left[O(C_h) + \sum_{i=1}^{n} (\lambda_{h,i} \cdot d_{h,i}) \right] \tag{4}$$

3.2. **Comfort model.** Smart home systems not only need to focus on the optimisation of electricity load, but also need to ensure the comfort of users. A reasonable comfort model can effectively improve user experience while avoiding the inconvenience and unnecessary energy consumption caused by frequent device switching and temperature adjustment.

The comfort model classifies and models the switching appliances and temperature control appliances in the smart home by collecting parameters such as indoor and outdoor temperature, light intensity and human activity.

3.2.1. *Comfort model for switching appliances on and off.* For switching appliances such as TV and lighting, the switching state of the appliance is determined by judging the light intensity and human activity in the past half hour, which is modelled as:

$$h_i = \begin{cases} 0, & \text{if } \int_{h-0.5}^{h} \Lambda_i L_i dt < \varepsilon \\ 1, & \text{if } \int_{h-0.5}^{h} \Lambda_i L_i dt \geq \varepsilon \end{cases} \tag{5}$$

where h_i denotes the switching on and off of appliance i during h hours; Λ_i denotes human activity; L_i denotes light intensity; and ε is the threshold value.

The comfort parameter for the number of electrical switches is:

$$t_1 = \sum_{i=1}^{m} \sum_{h=0}^{H} \mu_h \tag{6}$$

where m is the number of switched appliances. The higher the number of switches, the lower the comfort level of the user.

3.2.2. *Comfort modelling of temperature-controlled appliances.* For temperature-controlled appliances such as air conditioners and water heaters, they are controlled by introducing comfort metrics. Let the set temperature of the appliance be T_i, the indoor temperature be T_{in}, the outdoor temperature be T_{out}, the lower limit temperature be $\triangle T_2$, and the upper limit temperature of human comfort be $\triangle T_1$, and the comfort function is shown as follow:

$$\omega_i^h = \begin{cases} (T_{\text{in}} - T_{\text{out}} - T_i)^2, & \text{if } T_{\text{in}} < T_i - \triangle T_2 \\ 0, & \text{if } T_i - \triangle T_2 \leq T_{\text{in}} \leq T_i + \triangle T_1 \\ (T_{\text{in}} - T_i)^2, & \text{if } T_{\text{in}} > T_i + \triangle T_1 \end{cases} \tag{7}$$

The temperature control appliance is set off as a function of when no human activity is detected for half an hour:

$$v_i^h = \begin{cases} 0, & \text{if } \int_{h-0.5}^{h} \Lambda_i dt < \sigma \\ 1, & \text{if } \int_{h-0.5}^{h} \Lambda_i dt \geq \sigma \end{cases} \tag{8}$$

where σ is the human activity condition threshold.

The comfort parameters for temperature control appliances are shown as follow:

$$t_c = \sum_{i=1}^{n} \sum_{h=0}^{H} \nu_h \omega_h \tag{9}$$

where v_i^h is the on/off state of temperature control appliance i at time period h; and ω_i^h is the comfort function of temperature control appliance i.

3.2.3. *Multi-parameter comfort model.* Combining the comfort models of the above two types of appliances, the overall multi-parameter comfort model is shown as follow:

$$t = t_k + t_c = \sum_{i=1}^{m} \sum_{h=0}^{H} \mu_i^h + \sum_{i=1}^{n} \sum_{h=0}^{H} \nu_i^h \omega_i^h \tag{10}$$

3.3. **Multi-objective modelling of electricity price and comfort.** In smart home load control, it is difficult to meet the actual demand by only optimising a single objective of electricity price or comfort level. Multi-objective optimisation of electricity price and comfort can balance economic benefits and user experience, and improve the overall performance of the system.

Based on the aforementioned three-level tariff model and comfort model, a multi-objective optimisation model is constructed in this paper with the objective of minimising the total tariff and total comfort loss.

$$\min Q = \min(E + t) = \min\left(\sum_{h=1}^{H}\left[O(C_h) + \sum_{i=1}^{n}(\lambda_{h,i}\cdot d_{h,i})\right] + \sum_{i=1}^{m}\sum_{h=0}^{H}\mu_i^h + \sum_{i=1}^{n}\sum_{h=0}^{H}\nu_i^h\omega_i^h\right) \tag{11}$$

where E is the total electricity price; t is the total comfort loss.

4. **MPA solving multi-objective load optimisation control.** Based on the aforementioned multi-objective optimisation model, this paper will use MPA for solving. MPA is a bionic optimisation algorithm [27], which is inspired by the foraging strategy of marine predators, and has a powerful global search capability and fast convergence characteristics, as shown in Figure 2.

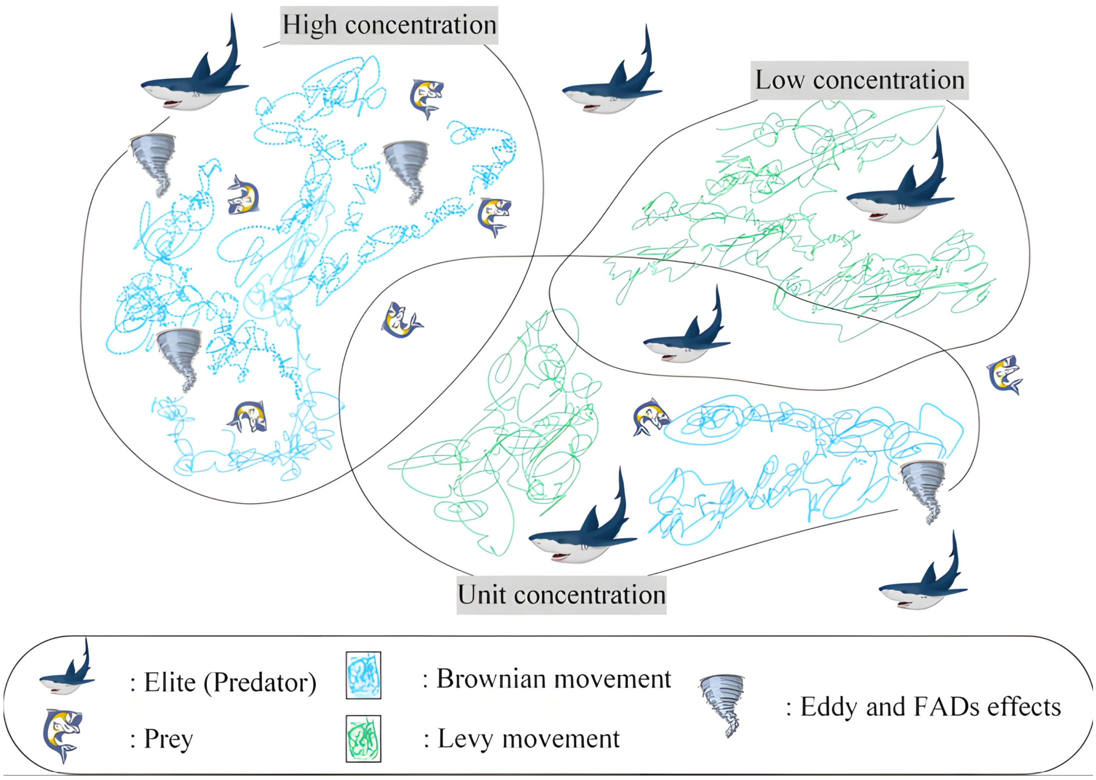

Figure 2. Principles of MPA

The MPA algorithm optimises the search by simulating the behaviour of marine predators in different predation stages, specifically including exploration, exploitation and stall phase. Each stage corresponds to a different search strategy to achieve global optimisation.

The population is first initialised to generate the initial solution population, along with the position and velocity of each individual:

$$X_i = X_{\min} + (X_{\max} - X_{\min}) \cdot \text{rand}(0, 1) \tag{12}$$

where X_i is the individual position; $X_{\min}$ and $X_{\max}$ are the upper and lower bounds of the search space, respectively; and $\text{rand}(0, 1)$ is a random number.

Calculate the comfort value for each individual. Evaluate the overall objective function based on the tariff and comfort model Equation (11):

$$Q_i = E(X_i) + t(X_i) \tag{13}$$

Exploration phase: individual positions are updated by simulating the behaviour of a predator searching for prey over a large area:

$$X_i^{\text{new}} = X_i + r \cdot (X_{\text{best}} - X_i) \tag{14}$$

where X_{best} is the current optimal individual position; r is a random vector.

Exploitation phase: simulating the behaviour of a predator searching finely for prey in a small area to further optimise individual positions:

$$X_i^{\text{new}} = X_i + r \cdot (X_{\text{mean}} - X_i) \tag{15}$$

where X_{mean} is the average position of the current population.

Stall phase: simulates the behaviour of a predator that stays around its prey and observes it in order to prevent premature convergence to a locally optimal solution:

$$X_i^{\text{new}} = X_i + r \cdot (X_{\text{best}} - X_{\text{mean}}) \tag{16}$$

Update the individual positions and the optimal solution based on the fitness value of the new position:

$$X_i = X_i^{new} \quad if\ Q_i^{new} < Q_i \tag{17}$$

The above steps are repeated until the termination conditions are met (e.g., the maximum number of iterations is reached or the fitness value converges).

The MPA solving multi-objective load optimisation control pseudo-code is shown in Algorithm 1.

In a multi-objective load optimisation control problem, the dimensionality of the problem usually depends on the number of power-using devices, the time dimension and the environmental parameters. In the case of this study, if the number of power-using devices is assumed to be n and the optimisation time period is T (e.g., every minute in an hour), then the problem dimension dim can be expressed as:

$$dim = n \times T \tag{18}$$

For example, if there are 10 electricity-using devices and the optimisation time period is 60 minutes (one time point per minute), the dimension of the problem is $10 \times 60 = 600$.

4.1. **Experimental environment and experimental data.** In order to verify the effectiveness of the multi-objective model and grey wolf algorithm proposed in this paper to solve the load control, simulation experiments were carried out using Matlab, with a computer environment of Windows 10 (64 bit), hardware configuration of Intel i7-6700HQ, and a memory size of 8 G. The setup of the cloud platform control system was also used to conduct the data collection and experiments in the field.

The experimental data are mainly from the real power load information of several household users in a region in August and September 2022, including indoor and outdoor temperatures, light conditions in the room and human activities. Among them, a part of

Algorithm 1 MPA for Multi-objective Load Optimization

Inputs: *pop_size* – population size, *max_iter* – maximum number of iterations, *dim* – problem dimension, X_{min} – lower bound, X_{max} – upper bound.

Outputs: X_{opt} – optimal solution, Q_{opt} – optimal value.

Initialize population $X = X_{min} + (X_{max} - X_{min}) \cdot \text{rand}(pop\_size, dim)$
Initialize fitness values $Q \leftarrow \infty(pop\_size, 1)$
$iter \leftarrow 0$
while $iter < max\_iter$ **do**
  for $i = 1$ to *pop_size* **do**
    $Q[i] \leftarrow E(X[i,:]) + t(X[i,:])$ ▷ Evaluate adaptation values
  end for
  Find current best Q_{best}, $best\_idx \leftarrow \min(Q)$
  $X_{best} \leftarrow X[best\_idx, :]$
  $X_{mean} \leftarrow \text{mean}(X)$
  for $i = 1$ to *pop_size* **do**
    if random number $r \in [0, 1] < 0.5$ **then** ▷ Exploration phase
      $X[i,:] \leftarrow X[i,:] + \text{rand}(dim, 1) \cdot (X_{best} - X[i,:])$
    else ▷ Exploitation phase
      $X[i,:] \leftarrow X[i,:] + \text{rand}(dim, 1) \cdot (X_{mean} - X[i,:])$
    end if
  end for ▷ Stall phase
  for $i = 1$ to *pop_size* **do**
    $X[i,:] \leftarrow X[i,:] + \text{rand}(dim, 1) \cdot (X_{best} - X_{mean})$
  end for ▷ Boundary handling
  Ensure X is within $[X_{min}, X_{max}]$
  $iter \leftarrow iter + 1$
end while
$X_{opt} \leftarrow X_{best}$
$Q_{opt} \leftarrow Q_{best}$
Return X_{opt}, Q_{opt}

the users are comparison users, and the designed multi-objective load control algorithm is not used to optimally control the electricity load. The other part of users are experimental users, which are configured with the cloud platform control system and the corresponding MPA algorithm.

The maximum number of iterations *max_iter* is 20 and the population size *pop_size* is 20. The experiment has 10 power consuming devices and the optimisation time period is 60 minutes, then the upper and lower limits of the search space are as follows:

Power range: 0 to 2000 W per device.

Temperature range: indoor and outdoor temperature range from −10 to 50 °C.

Light intensity range: 0 to 1000 lux.

Thus, the problem dimension *dim* is 600 and the upper and lower bounds of the search space X_{min} and X_{max} are [0, −10, 0, ...] respectively and [2000, 50, 1000, ...].

4.2. **Simulation results.** In this paper, the experimental simulation is carried out for both single target and dual target (tariff and comfort) cases of electricity price. Figure 3 compares the simulation of the consumer electricity load data for both single target and multi target cases. It can be seen that both methods effectively reduce the load of electricity consumption and effectively save electricity. With the change of time, the electricity load will have obvious fluctuations, which is in line with the daily electricity consumption habits of users. Among them, the electricity load reduced by multi-objective control is lower than the electricity load reduced by electricity price single objective. This is because multi-objective control also needs to take into account the user's comfort, which needs to be at the expense of increasing the electricity bill, for example, reducing the number of times electrical appliances are switched on and off, and increasing the air-conditioning temperature. The algorithm is able to control the load more effectively and reduce the energy consumption during some of the electricity peaks. Figure 4 shows the comparative analysis of single and multi-objective on human comfort, and it can be seen that multi-objective control ensures better user comfort compared to single-objective control of electricity tariffs.

Table 3. Simulation results of different control methods

Control mode	Average load/kW	Comfort
Not have	3.57	0
Single-target control	2.33	3.1
Multi-objective control	2.79	11.3

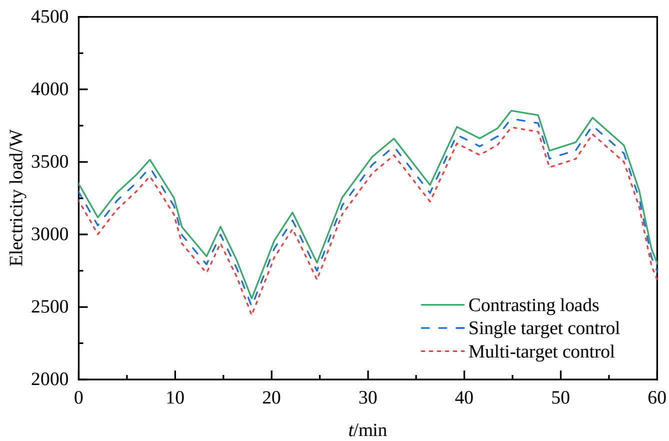

Figure 3. Simulation of power load

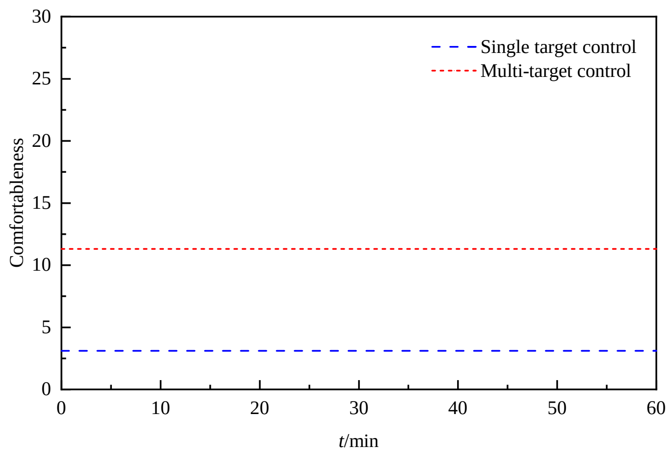

Figure 4. Comparison of comfort results

The simulation results of the average data for different control methods are given in Table 3. It can be concluded that the single objective control method in order to reduce the average load from 3.57 kW to 2.33 kW, whereas multi-objective control reduces the average electrical load from 3.57 kW to 2.79 kW. The factor of average human comfort is 3.1 when the control is performed by the single objective, whereas the human comfort is highly improved with the use of multi-objective control, with an average comfort of 11.3.

5. **Conclusions.** In this paper, a multi-objective optimal control method for smart home loads based on IoT and MPA is proposed to address the shortcomings of the existing load control methods in terms of taking into account the cost of electricity consumption and user comfort. Through IoT technology, the system is able to monitor the home environmental parameters and electricity consumption data in real time and upload them to the cloud platform for processing and analysis, which achieves the continuity and real-time data collection. The MPA algorithm is used for multi-objective optimisation, thus efficiently reducing the cost of electricity consumption and improving user comfort. In the single-objective control experiment, the system mainly optimises the electricity price, and the results show that the average electricity load is reduced from 3.57 kW to 2.33 kW, which saves a large amount of electricity cost. However, this optimisation method fails to effectively consider user comfort, resulting in a user comfort index of only 3.1, indicating a poor user experience. In contrast, the multi-objective control method not only optimises the electricity price, but also takes into account the user's comfort. The experimental results show that the smart home system with multi-objective control reduces the average electricity load from 3.57 kW to 2.79 kW, and although the savings in electricity price are relatively small, the user comfort index is significantly improved to 11.3. This result suggests that the MPA approach is able to better balance the economic benefits and the user experience by considering both the electricity price and the comfort level in the optimisation process. Future research can further optimise the MPA algorithm to improve its applicability to larger datasets and more dimensional load control problems. Meanwhile, other advanced group intelligence algorithms can be explored to develop more efficient load optimisation control methods for smart homes by combining them with IoT technology.

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