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Home Energy Optimization Based on Wearable Devices

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The power consumption is related to people's level of comfort. In this paper, we propose a home power optimization method based on the sensing data obtained from wearable devices. More specifically, we analyse the user behavior based on this sensing data, and we use a neuron network to establish the mapping between user behavior and level of comfort. We model a home system and propose a smart home energy optimization method based on model predictive control. We design a smart home energy optimization prototype, and design four scenarios to verify our proposed method.

Keywords: energy efficient, wearable devices, smart home, user comfort, model predictive control (MPC)

1. INTRODUCTION

Household space is an important physical area for humans and their activities. The development of science and technology and the rapid increase of social informatization and networks have led people to demand that their household space be more than just a place where they rest; they want it to be a safe, intelligent, convenient and comfortable home environment. The 'smart home' concept is based on the electronic technology designed for the household. The notion of an intelligent household emerged in the 1980s due to the gradual automation of household appliances and devices. Today's intelligent household comprises a combination of advanced electronic, computer, network communication, and automated and intelligent technologies, intended to achieve two goals: to improve the user's comfort and reduce energy consumption [10].

The improvement of user comfort is one of the primary goals of a smart home. Since 1987 when the world's first intelligent building was constructed in the US, all countries in the world have put forward proposals for smart homes, one of which is Bill Gates' famous 'intelligent mansion'. The smart home solution involves the acquisition of detailed information and equipment that provides centralized control of the data. In the current smart home platform, it is important to find a way to respond intelligently to the user's demand for the comfort of the home environment, which requires determining the effective control target of the home environment that meets the user's comfort requirements [11].

The energy problem, which is a major issue in the 21st century, has made it imperative to develop a smart home that reduces energy consumption and carbon emissions. The proportion of household power consumption accounts for the total power consumption, and studies have shown that this is due to poor efficiency and serious waste of electricity. In addition to the smart grid adopted by householders, a smart home has other requirements including a smart home energy management system. Currently, this is an important part of the development of the intelligent household. By analyzing the data captured by a smart home sensor network, the intelligent electrical equipment can optimize the scheduling of appliance so as to ensure the householder's comfort while improving the efficiency of electricity and reducing power consumption.

The smart home energy optimization problem is becoming a hot research topic, but faces three challenges: 1) it is difficult to meet the user's comfort requirements because they are personal and uncertain. The optimal control of electrical equipment depends on subjective factors such as the person's mood, exercise behavior, and body condition, to name a few. Most of the existing methods do not take these factors into account, but mainly use the householder's

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setting or statistical historical data as the control target, which will have a negative impact on the control result in practical application. 2) Because the household environment has individual differences, and the characteristics of stochastic dynamics in buildings, factories, and other areas require energy optimization, there is a need to build an accurate environment model based on room structure, and building features such as wall materials that may be limited by cost and privacy issues. All of these factors make it difficult to develop an intelligent household system model that is customized for each user. 3) The optimization of smart home energy is a multi-stage problem involving several random factors. Whether the user is at home or outside, and the change in user demand will affect the control strategy applied to home appliances.

Based on the intelligent home furnishing platform, this paper proposes a user-centered smart home energy management method that takes as input the data obtained by wearable sensing devices. This data enables the analysis of user behaviors, user position, and motion state and body state. The mapping of user behavior to user comfort demand is done by means of a neural network. The system model of easy extension and universalization is established, and the system parameters are estimated dynamically using the sensor network data of the smart home. Based on the model predictive control (MPC) of the smart home's energy optimization, the uncertainty of user behavior is taken into account and the system responds dynamically to the user's comfort needs. In this paper, a system is proposed whereby smart home energy management takes into account the user behavior and comfort requirements in terms of perception and response to uncertainty. This household system model of system delivers personalized optimal power to ensure the economic efficiency of energy, efficiently reducing power consumption and greatly improving the comfort of users.

2. RELATED WORK

The intelligent home is a residential environment with a high level of efficiency, comfort, safety, convenience and environmental protection, which is based on the residential platform and equipped with automated household appliances controlled by network communication and data input [12], integrating system structure with service management. The original smart home contained electronically-controlled household appliances that were practical and more convenient. Yang et al. (2016) designed and implemented a Java-based automation system, which is integrated on an independent embedded system of a home server and can monitor and control the home devices centrally. On the other hand, Shweta and Shruti (2017), proposed a control home appliance system based on a PC Bluetooth automation system. Along with the development of the Internet of Things (IoT), the wide application of wireless sensor networks and data-gathering devices, an intelligent household consisting of a large sensor network and calculation system provides household system monitoring, entrance security, data acquisition and intelligent control. Srilakshmi et al. (2021) designed a sensor network platform that enables accurate detection of all objects in indoor spaces.

A smart home is an extension of the smart grid used by residents, and has become an important element of the smart grid electricity link. Based on the smart grid concept, the smart home, can improve the efficiency of householders' energy consumption, strengthen the demand side response peak by reducing the controllable load, and become the new requirement of a household system. Based on the smart home network platform, the smart home system optimizes the scheduling of household appliances and has become a new trend in the development of smart home [13]. The earliest literature [8] investigated the energy requirements of commercial buildings and proposed the optimization of energy supply and the scheduling of activities in the manufacturing sector.

The studies conducted by Qinwei (2016) and Yutaka et al. (2014) were from the residents' perspective, and proposed ways to improve energy efficiency in order to take full advantage of the power grid. However, their work did not take into account the behavior of the smart home system users' behavior, nor the uncertainty of their comfort demands. They proposed systems where the comfort requirements of users were set as a specific value. The system responding to the user's comfort demands should be user-centric. However, because individuals are r required level of comfort depends on several factors that can be personal, or in both the inside and external environments, it is difficult to design an intelligent system that optimizes energy efficiency.

A great deal of research has been conducted on the user's demand for comfort in a smart home. For instance, Srilakshmi et al. (2021) proposed an adaptive smart home system using machine learning algorithm to learn user's daily activity pattern. HeZhong et al. (2009) designed a programming thermostat that uses data to automatically and more efficiently run air conditioners. Jean & Anders (2014) proposed a non-intrusive load monitoring system that collects and analyzes user behavior and energy-consumption patterns. Wenpeng et al. (2015) proposed a system whereby the user's power consumption can be analyzed and appliances can be scheduled to operate accordingly. These methods are based on historical user behavior data, with statistics applied to ensure optimal control and user comfort with minimum energy consumption. However, this method cannot be applied to the smart home user who is an individual with unpredictable behavior and needs. Therefore, by not taking into account the personal characteristics of the user, the aforementioned systems could lead to unnecessary energy consumption [14].

3. SYSTEM MODEL

In order to address the uncertainty of user behavior and comfort demand in a smart home system, this paper proposes a smart home energy optimization method based on the analysis of sensor data captured by wearable devices. The proposed system is shown in Figure 1:

A user's wearable device sensor can accurately capture the location of the smart home user, his/her physical state, and behavior when at home. At the same time, environmental sensors in the smart home system monitor the temperature and

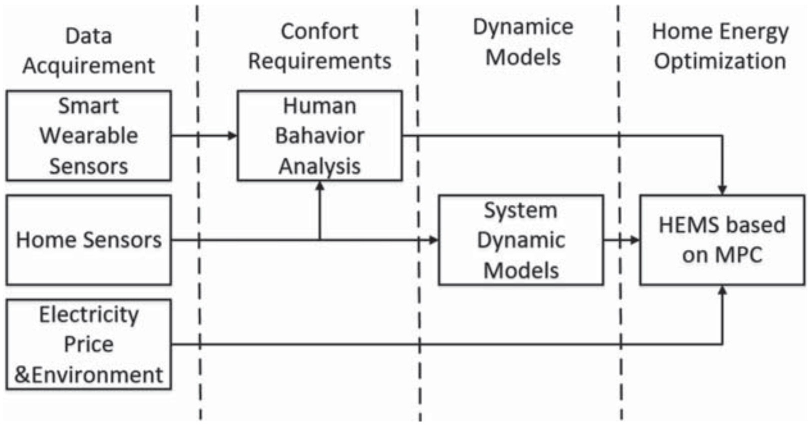

Figure 1 The methodology of smart home energy optimization.

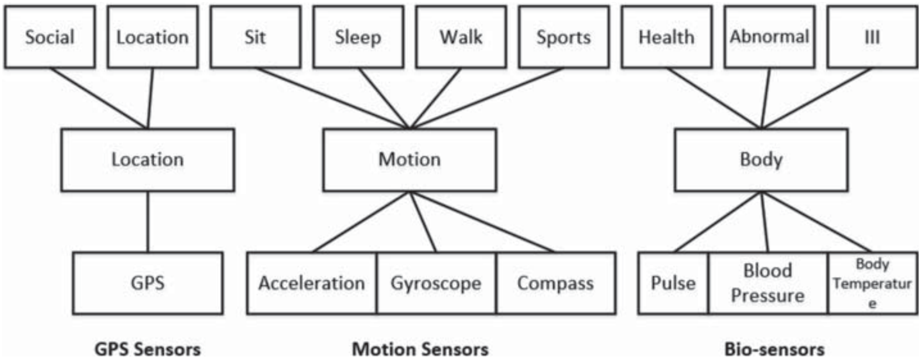

Figure 2 Human behavior analysis based on wearable devices.

humidity, and light sensors collect data related to electrical appliances, and environmental information, such as the state of the household system. According to the perceived user behavior and the state of the home system, mapping ofrelations is used to estimate user comfort requirements. At the same time, the data for the home system status is used for the dynamic modeling of the user's home system. Based on the updated dynamic model of the home system that takes comfort needs and the home system's status into account, MPC is used to optimize the efficiency of household energy consumption, and obtain the optimal control of the home system that meets the user's comfort requirements.

3.1 Analysis of User Comfort Requirements Based on Wearable Devices

With the rapid development of mobile Internet, wearable devices have become a feature of many people's daily lives. Common wearable or portable devices include smartphones, smart and intelligent bracelets and watches etc. Importantly, these wearable devices are equipped with a variety of sensors to capture position (GPS sensor) and motion, and biosensors and environmental sensors and so on. These sensors pick up data that are analyzed to give an accurate picture of user behavior and comfort requirements.

In this paper, an analysis of user behavior data acquired by wearable devices is proposed. Figure 2 depicts the analysis of data obtained by the position sensor, motion sensor and biological sensor. In addition, the environmental sensor is used to record the user's environmental data. The four sensors are described below.

1) Position sensor: this retrieves information about the user's location, including the x/y coordinates, movement speed, data such as tag, buildings close to the user such as offices, sports and shopping venues, residential areas. A database is constructed that establishes the location of the (device) wearer, including the proximity to buildings such as the workplace, sports facilities, etc. which can indicate the user's activities and interests.

2) Motion sensor: this includes an acceleration sensor, gyroscope, electronic compass sensor and so on, and captures typical user movement behavior such as sitting, lying down, walking, running and other behaviors. Different movements will have different comfort requirements. This sensor extracts the acceleration and direction data, matches and classifies the motion sensor data, and analyzes the user's movement behavior.

3) Biosensor: common biological sensors can capture data related to temperature, and blood pressure, among other health indicators. biosensor data can be used not only to determine and analyze a person's movements, but can also indicate health status. Movement and physical status are closely related to biological characteristics. For example, data rapid pulse may suggest that the user is exercising too strenuously, a slow pulse indicates that

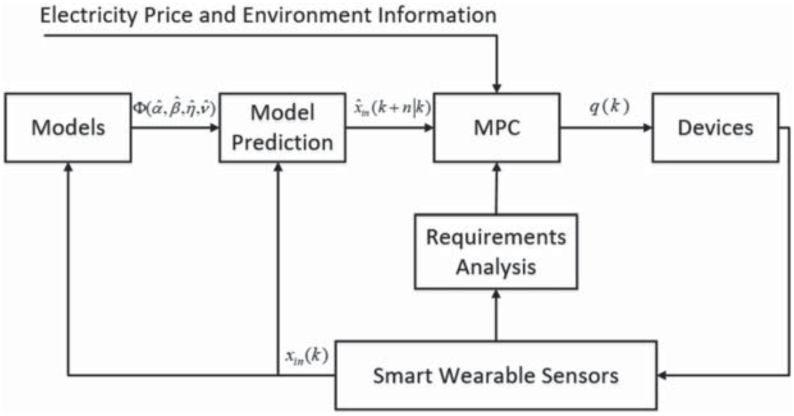

Figure 3 Smart home energy optimization based on MPC.

the users is asleep, and the body temperature can indicate whether the user is sick, or whether the user is too hot or too cold [1]. The expert system can set parameters to determine a wearer's activities and physical state.

4) Environmental sensors, including temperature and humidity sensors, atmospheric pressure sensors and environmental light sensors, are used to capture the data related to the user's environment.

3.2 Analysis of User Comfort Requirements

To create an efficient, smart household system that minimizes energy consumption while meeting the user's comfort requirements, several factors must be taken into account: the household environment, the parameters set for environmental control of appliances in terms of operating times, user comfort requirements that determine when appliances will operate (e.g. water heating and air conditioning), and the user's mood, exercise behavior, health, environment and other factors. The user's comfort requirements are determined by analyzing user behavior and establishing comfort mapping based on the perceived user behavior data.

1) Demand period analysis

   Here we assume that a householder expects the home environment to be comfortable and have an ideal temperature, and access to adequate hot water and other utilities. It is unlikely that a rational person would want anything less. In this regard, the position sensor and the analysis of the user's location data can accurately determine whether the user is at home, and then adjust the user's comfort requirements accordingly to prevent electrical appliances from operating in the householder's absence, which would incur unnecessary costs and power wastage.

2) Analysis of environmental parameters of demand

Movement behavior, body state and environment can directly affect the temperature which can determine the user's level of comfort. However, this involves complicated and nonlinear mapping, and it is also difficult to perceive and predict the impact of data such as the person's mood, emergencies, etc. The back propagation (BP) neural network can approximate a nonlinear mapping with a degree of accuracy, can learn and adapt unknown information, and has a certain fault tolerance, suitable for dealing with a complex problem. This paper applies the commonly-used BP constructs to map the relationship between a user's movement behavior, body state and environment data and the user's comfortable temperature demand. A sample of the household environment data based on the user's comfort, is used as the training sample to study the established BP neural network, When the user feels uncomfortable in the current household environment, data can be sent via a smart phone terminal showing that the environment is not satisfactory or being properly controlled manually. When the user is feeling uncomfortable, this information is collected by all the sensors embedded in the wearable device. Because the user's complaint about the temperature is unidirectional, namely when the temperature in the user's environment is greater than his/her physical temperature, and vice versa, the user feels discomfort. The training sample can obtain the parameters for the temperature level that is uncomfortable.

3.3 MPC-Based Smart Home Energy Optimization

Smart home energy optimization combines the dynamic electricity price, environmental prediction information released by the power grid and the dynamic comfort demand of users based on the data obtained by wearable devices to optimize the efficiency of electricity consumption and ensure the comfort of users. The control strategy of the device minimizes the operational cost of the smart home system. In order to deal with the uncertainty of user behavior and the change of system dynamic characteristics, this section optimizes the scheduling of electrical equipment based on MPC. The method architecture is shown in Figure 3.

MPC (model-based predictive control) describes a set of advanced control methods, which make use of a process model to predict the future behavior of a controlled system. It consists of a limited time domain closed-loop optimal control algorithm based on the model, and real-time monitoring of the system which addresses the issue of uncertainty. In this paper, MPC is used for the optimization problem; the data for the household temperature and the user's behavior was collected by the wearable sensor device and household environment observations. The collected data is used to model parameter calibration system, and forecast the future state of the system. Moreover, it is used to update the user's comfort requirements. The system can change and adjust the indoor temperature environment in real time according to the user's indoor temperature requirements to meet the user's comfort requirements, in order to avoid the model error and the eff ects of environmental interference, the control strategy is set to only one hour.

Algorithm 1. MPC-based intelligent home energy optimization solution.

Output: at the moment k, the electrical control strategy $q(k)$.

Step 1. At the moment k (the initial value is 1, which is the initial scheduling moment). For temperature state $x_{in}(k)$, observing data from wearable sensors and home environment sensors, updating system model $\Phi(\hat{\alpha}, \hat{\beta}, \hat{\eta}, \hat{v})$ and user comfort requirements $R\{z, \overline{T}\}$, state information is predicted based on dynamic system models $\hat{x}_{in}(k-n|k)$.

Step 2. Solve the following optimization problems and obtain the energy consumption of household appliances $\hat{q}(k)|_k^{K-1}$:

$$\min J = \sum_{k}^{K-1} p(k)\hat{q}(k) \tag{1}$$

$$s.t. x_{in}(k+1) = \alpha x_{in}(k) + \beta x_{out}(k) + \eta\hat{q}(k) + v \tag{2}$$

$$0 \le \hat{q}(k) \le q_{\max} \tag{3}$$

$$\overline{T} - \Delta \le x_{in}(k) \le \overline{T} + \Delta, \ \text{if} z(k) = 1 \tag{4}$$

where the optimization target represents the electricity consumption cost generated by the household appliances during the optimization period; in the state transition equation, $x_{in}(k)$ is the state observation time k. This optimization problem is linear and can usually be solved with linear programming.

Step 3. Apply the value of the optimal solution start time to the system, $q(k) = \hat{q}(k)$.

Step 4. Let $k = k + 1$ and return to step 1 until $k = K - 1$.

This completes the real -time optimization solution based on MPC. Then, the optimal household equipment power consumption sequence can be obtained for the entire optimization period, wherein each power consumption value indicates the average power consumption that is not accounted for in the unit scheduling period. The control terminal of the smart home can be based on the actual power consumption of the appliances. The error of the system model and the influence of uncertain personnel behavior and environmental factors can be monitored in real-time. The proposed system model can be adjusted and has strong robustness.

4. SYSTEM DESIGN

In this paper, a smart home experiment platform is set up, and includes typical home appliances, a home environment sensor and intelligent switch. At the same time, the platform supports variety of intelligent devices (including smartphones, bracelets, watches etc.) associated with the optimization of a smart home energy system. The system consists of three main modules: intelligent mobile terminal, application gateway and energy optimization services.

A typical household environment is used for the experimental simulation platform, and involves the installation of commonly used appliances such as an air conditioner, water heater, refrigerator, television, lighting equipment, washing machine, etc. All electrical equipment is controlled by a control terminal end: for electrical appliances with infrared control ports, such as empty television, etc., the infrared control signals are transmitted directly from the control terminal. Other appliances and devices are controlled by the intelligent switch through the wireless network and terminal-end connection machine. At the same time, the experimental platform deploys an environment sensor network, including the temperature, humidity, and light sensors. These sensors acquire real-time data on the household environment, and the data is transmitted via a wireless module.

Smartphone is a mobile terminal device that can run multiple applications at the same time, and it can collect and transmit data. Remote controls, information displays, Bluetooth, and Wi-Fi wearable devices can all be connected to smartphones, and feedback information to clients through smart gateways and servers. The smart phone client also has a design control page enabling the user to select the appliance and send a command to control the function of the appliance or equipment. At the same time, the smartphone client can view a great amount of data on the screen, such as real-time information about the smart home environment, the appliance status, and the cost of the energy being consumed.

The intelligent gateway, a key element of the smart home system, is responsible for the task of gathering information fr om different parts of the network. The external network is connected to the smartphone via the Internet. All the data acquired by the smartphone and the home environment sensor network is transmitted to the energy optimization server through the smart network switch. Device control commands sent by energy optimization servers and the smartphone are also sent to smart gateways.

A smart home energy optimizing server is a central part of the smart home system, a smart phone gives access to data in the energy smart home sensor network management server to process and analyze user behavior, estimate comfort requirements, establish a system model for the user's home and optimize problem solving by controlling the function and status of household appliances and equipment. Here, the intelligent control of appliances such as the air conditioner and water heater has energy-saving potential, and intelligent optimization can be based, intelligent optimization server intelligent generation control strategy based on user comfort demand. Permanently-fixed appliances such as televisions and refrigerators, can be controlled remotely by the user via the smartphone.

5. EXPERIMENT AND ANALYSIS

This section includes a description of the experimental smart home platform, an analysis of the experimental results, and the

Table 1 Specific parameters.

Scenario 1		Scenario 2		Scenario 3		Scenario 4	
Time	**Event**	**Time**	**Event**	**Time**	**Event**	**Time**	**Event**
09:00	Leave Home	09:00	Leave Home	09:00	Leave Home	09:00	Leave Home
16:30	Regular Event	14:00	Accidental Event	17:30	Traffic Jam	16:30	Sports
17:00	Back Home	15:00	Back Home	20:00	Back Home	19:00	Back Home
22:00	Sleep	22:00	Sleep	22:00	Sleep	22:00	Sleep

evaluation of two optimization performance indicators: the costs of operating household appliances, and the optimization of user comfort. Because user behavior within the home can be unpredictable, the optimal performance of the system was analyzed under different user behaviors. This experiment simulated the user's daily behavior, constructs four typical and regular human behaviors, and irregular behaviors such as early return from work, late return due to overtime, traffic etc., and activities such as sports or socializing. Specific parameters are shown in Table 1 below.

In the experiment, the rule-based control strategy (manual user control) and the optimization control method proposed in this paper were compared. When a user is at home, s/he starts the household appliances or sets the controller so that an appliance starts to operate at a certain time. This is a common way of controlling appliances via smart home devices, and in effect is a manual control system. For example, the user may control an air conditioner's operation by setting a certain temperature, and the appliance ensures that this indoor temperature is maintained by automatically switching on and off.

In the experiment, the day-ahead optimal scheduling strategy was not applied, mainly because it cannot respond to the unpredictability of user behavior, environmental conditions and model dynamics in the home system, and it would be difficult to update the user's comfort requirements.

In the experiment, a moderate user's temperature demand was set at 22:00, based on the assumption that a person's comfort range will be between 2:00 and 3:00 on either side of the set temperature. Hence, the temperature was set within 21:00 to 23:00 for basic comfort demand intervals.

In scenarios 1, 2 and 3, the optimization strategy based on MPC and the control strategy based on rules are compared according to the different behaviors of the user at home. The results show that the optimization strategy based on MPC performs well in terms of perceiving and responding to changes in user behaviors, demonstrating that the proposed control strategy can guarantee the user's maximum comfort.

The user's movement behavior in scenario 4 is based on scenario 3. The movement behavior is captured by the motion sensor and biological sensor data is acquired by the wearable device. The data is analyzed to determine the user's comfort demand. In this scenario, the MPC-based optimization decision reflects the change in the user's dynamic after-hours comfort requirements in the home at 19:00 and during sleep time when the user has different comfort requirements. There is no same user delay behavior in the scenario 4, and in this scenario 3, the operation of the air conditioner leads to a waste of power. ,The reason is that the energy of the air conditioner wasted in the scheme 3 was caused by the user's home late and did not turn off the air conditioner in time, and the operation of the air conditioner was not detected in the family. On the other hand, the sports behavior of the user in scenario 4 (16:00) can be easily detected from location data which indicates a sports facility, as well as the user's delay in returning home.

5.1 Perormance Evaluation of Optimization Strategy

In this section, the levels of efficiency and comfort are used to evaluate the performance of the two kinds of control strategies.

1) The economic efficiency index is calculated by 1 d operation with the charge for electricity being an objective function of the optimization problem as this is an important factor in the optimization strategy. The cost of the electricity consumption in each of the four scenarios is shown in Table 3.

2) User comfort is an essential consideration in an intelligent household energy optimization system. Therefore, we determine the comfort level in order to evaluate an optimization strategy for comfort.

It can be seen from the two performance indicators that the proposed MPC-based optimization strategy achieves the best performance for comfort in all scenarios. In scenarios 1, 2 and 4, the results obtained by the proposed strategy are compared with the rule-based control strategy, and indicate that the MPC-based optimization strategy can save over 20% in electricity costs. This shows that under the proposed smart home energy optimization method, the MPC-based optimization strategy can timely respond to users' uncertain behaviors and changes in comfort requirements to ensure user's maximum satisfaction. Rule-based control strategies have set comfort requirements and appliances can be controlled only when the user it at home. The rule-based control strategy is a conservative control approach that is unresponsive to user behavior. It should be noted that for scenario 3, the MPC-based optimization strategy and the rule-based control strategy incur similar electricity costs, saving 13%. This is because in the scenario 3, the user does not go home in time, and the air conditioner is turned on prematurely for the comfort of the indoor space, resulting in a waste of electricity.

The experimental results indicate that the intelligent household energy optimization system proposed in this paper can sense and respond to changes in user behavior, and that the optimization strategy based on MPC is an efficient way to meet user needs. And so, the user will not determine the behavior of the cow is more scenarios, optimization strategy based on the method system to ensure that meet the demand of the user comfort can lead to the rise in electricity costs in this scenario, however, does not respond to user behavior relative to the conservative control strategy. The performance of the comfort level will be greatly improved. Although the economic performance of the optimization strategy also depends on the factors such as setting electricity price and environment in the accurate scenario of user behavior, this experiment still reflects the advantages of the smart home energy optimization method proposed in this paper in terms of both economy and comfort.

6. CONCLUSION

The goal of the smart home is to improve user comfort while ensuring the energy efficiency of home appliances. However, smart home design faces the challenge of individual user demands and unpredictable changes in user behavior. This paper is the first to propose a smart home energy management system that uses a wearable sensor device to collect and analyze data. This addresses the issue of users' unpredictable behaviors and individual needs so that electrical home appliances can be controlled optimally to ensure the user's comfort in the home environment, and the lowest energy costs. The proposed intelligent household simulation platform and the design and implementation of a smart home energy optimization system, showed that the system developed in this paper can effectively reduce the cost of electricity. The system developed in this study can be installed on the Android platform, mobile smartphones and other terminals, and connected to other wearable devices (such as smart bracelets, smart watches), combined with intelligent infrared control equipment to control the functions of common household electrical appliances. This application of the Internet to the running of a household has good market prospects.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest to report regarding the present study.

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