

# Network Architecture Design of Intelligent Housing Energy-Saving Systems Based on Internet of Things Technology

Hui Liu<sup>1,\*</sup>

<sup>1</sup> School of Internet, Henan Mechanical and Electrical Vocational College, Zhengzhou, Henan, 451191, China

Corresponding authors: (e-mail: [wagkathleen@126.com](mailto:wagkathleen@126.com)).

**Abstract** This paper proposes a network architecture design for an intelligent residential energy-saving system based on IoT technology. The perception layer is constructed using ZigBee technology, while remote monitoring is achieved through Internet and GPRS technologies. The system encompasses functions such as residential security, intelligent control of lighting and temperature, individual household heat metering, and electricity consumption monitoring. An electricity consumption optimization model based on an improved genetic algorithm is established. Through field testing and data analysis, the effectiveness of the system in thermal environment regulation and energy consumption optimization is validated. During the cooling season, the largest proportion of indoor temperatures in smart housing is 26°C, accounting for 26.5%. In conventional housing, the largest proportion of indoor temperatures during the cooling season is 28°C, accounting for 17.5%. The relative humidity range in smart housing is slightly narrower than in conventional housing. During the heating season, the indoor thermal environment in smart housing remains significantly superior to that in conventional housing, and the IoT system significantly reduces the duration of humidity exceeding standards. Energy-saving benefits decrease as the proportion of factors increases, from 3% at 4,629.52 yuan/m<sup>2</sup> to 13% at 2,023.47 yuan/m<sup>2</sup>, indicating that the economic benefits of reducing energy consumption decrease as the energy-saving proportion increases.

**Index Terms** IoT, smart housing energy-saving system, improved genetic algorithm, power energy consumption optimization

## I. Introduction

In the context of the internet era, the energy-saving systems of smart homes have laid an important technological foundation for achieving energy conservation and reducing pollution. This is inseparable from the development of smart homes and the enhancement of energy conservation and emissions reduction awareness [1]-[3]. Smart housing has emerged as a natural product of the information age, shaped by the advancement of intelligent technologies, societal progress, and the growing, evolving, and refining needs of people [4]-[6]. For China, designating “energy conservation and emissions reduction” as a key objective during the 11th Five-Year Plan period has driven a nationwide increase in awareness of energy conservation and emissions reduction [7], [8].

Smart housing energy-saving systems based on IoT technology connect various home appliances to the internet, enabling interconnectivity between devices and providing users with more convenient and intelligent living experiences [9]-[11]. In terms of energy management, IoT-based smart housing energy-saving systems can monitor and control household electricity usage through smart meters, smart outlets, and other devices, helping users use energy efficiently and reduce waste [12]-[14]. In addition to energy conservation, IoT-based smart home energy-saving systems offer numerous advantages over traditional home appliances [15]. First, they provide remote operation and monitoring capabilities, allowing family members to control and monitor home appliances anytime, anywhere via mobile devices, eliminating time and location constraints [16], [17]. Second, IoT-based smart home energy-saving systems can achieve interconnectivity between devices, enhancing their collaborative capabilities and achieving higher levels of automation [18]-[20]. Additionally, the system can utilize big data analysis and artificial intelligence technology to provide personalized intelligent services based on users' habits and needs [21], [22].

This paper first proposes a multi-layer framework consisting of a perception layer, a network layer, and an application layer in the system architecture design section. ZigBee technology is adopted to achieve flexible networking, and embedded gateways are used to replace traditional servers to reduce costs. The paper provides a detailed explanation of the data collection and device linkage mechanisms for temperature, humidity, and light sensors, and combines household heat metering technology to achieve community-level energy-saving control. For building power consumption monitoring, a sub-metering scheme is proposed, and an improved genetic algorithm is used to establish an optimization model. Through field tests, the thermal environment of smart housing is compared

with that of conventional housing to validate the superiority of smart housing. The energy consumption level of smart housing is assessed to verify the optimization effectiveness of the proposed model.

## **II. Design of an intelligent housing energy-saving system based on Internet of Things technology**

With the rapid development of IoT technology, smart housing systems have shown great potential in improving living comfort and energy efficiency. This paper focuses on the design of IoT-based smart housing energy-saving systems, with an emphasis on addressing the shortcomings of traditional housing in energy consumption management and environmental control.

### **II. A. Overall Design of Smart Housing Energy-Saving Systems**

The subject of this study is smart and energy-efficient residential buildings. In terms of smart functionality, this system employs ZigBee technology for indoor networking, which is highly suitable for residential use due to its flexible networking capabilities. The external network is realized through two methods: the Internet and GPRS. Users can monitor the residential building using smart terminal devices. The gateway responsible for protocol conversion between the three systems uses an embedded system instead of traditional dedicated PC servers, thereby enhancing system reliability, reducing system size, and lowering energy consumption and costs. This enables functions such as residential security, intelligent lighting control, intelligent temperature control, and automatic alarm systems. In terms of energy conservation, the residential heating individual heat metering system is used to achieve energy-saving control across the entire community; simultaneously, the intelligent monitoring system for residential equipment enables itemized metering of indoor electricity consumption and effectively reduces standby energy consumption.

In summary, the smart and energy-efficient residential system consists of the perception layer, network layer, and application layer.

### **II. B. Building the system perception layer based on ZigBee technology**

The function of the lighting and temperature automatic control subsystem is to collect lighting and temperature data from inside the residence, control the brightness of indoor lighting and the opening/closing of curtains to achieve optimal visual effects, and simultaneously control the individual heating metering devices and air conditioning equipment within the residence to maintain a comfortable indoor temperature.

The sensing layer nodes of this subsystem consist of temperature and humidity sensors, light sensors, relays, infrared transmitter modules, and ZigBee modules. By collecting indoor light and temperature/humidity data and transmitting it to an embedded web server for processing, while receiving the server's processing results and controlling and adjusting home appliances and heating water valves. The working principle of this subsystem is the same as that of the health monitoring subsystem and the remote control system for information appliances. Additionally, this subsystem includes residential heating metering functionality, with each household as a unit, applicable to an entire building or even an entire community. Each household is equipped with a dedicated heat meter, installed at the user's entrance for heat measurement. Through the autonomous and automatic regulation functions of the thermostatic valves installed on the radiators, the flow rate of hot water through the radiators in the household heat metering heating system varies, resulting in variable flow operation on the load side of the heating system.

### **II. C. IoT-based building power consumption monitoring**

#### **II. C. 1) Overall Design**

IoT-based building power consumption monitoring requires the collection of power consumption data within a building without affecting the operational efficiency of the various devices within the building. A system has been designed to monitor the power usage of a building, which consists of three main components: information collection terminals, network communication terminals, and a centralized management unit.

The information collection terminal uses Zigbee technology to monitor the real-time status of on-site equipment. The network communication unit collects status information from each device, sends it to the network communication unit for processing, and obtains data such as operating time, current, voltage, and power from each device within the building. This data is then transmitted to the centralized management unit, which analyzes and processes the data to determine the comprehensive energy consumption of each device within the building and transmits the energy consumption data to the energy management system. Design of a building power energy consumption data collector. The structure of the information collector is shown in Figure 1.

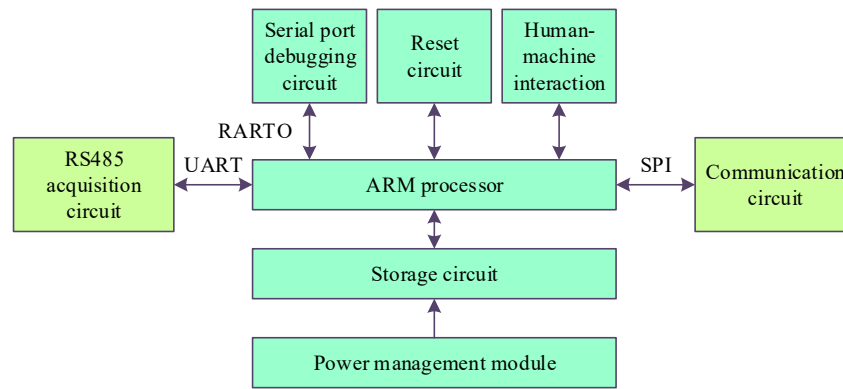


Figure 1: Structure of information collector

With the support of the data collector, the data acquisition module uploads monitoring data to the data center for further analysis. To ensure communication security, data transmitted between the collector and the data center is exclusively in XML format, and authentication information is configured only once per communication session. Under normal conditions, the collector maintains a stable connection with the data center. In the event of network failures or other unexpected issues, the collector activates its self-configuration functionality to perform a reboot and self-diagnosis. The self-configuration process of the data collector is shown in Figure 2. By utilizing the self-configuration function to achieve automatic configuration of the data collector, data loss caused by network abnormalities is avoided during the monitoring of building electricity consumption. After obtaining the monitoring data, an improved genetic algorithm is used to establish an optimization model for near-zero energy buildings, with the monitoring data as input for solution, to evaluate the building's electricity consumption level and energy-saving control.

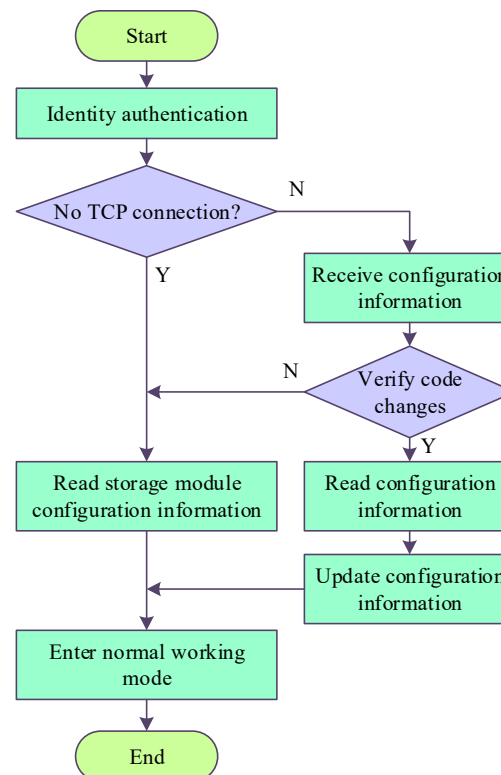


Figure 2: Schematic of self configuration process of collector

## II. C. 2) Basic formulas for heating regulation

Operational adjustment refers to the regulation of flow rate, supply and return water temperature, and other parameters in a heating system to achieve demand-based heating when the heat load changes. In heating systems, the variation in heating load with outdoor temperature is generally used as the basis for network operational adjustment. The primary objective of heating system operation regulation is to maintain indoor temperatures within the calculated temperature range during the heating season, thereby preventing excessive or insufficient temperatures that could adversely affect user comfort.

Under normal circumstances, if the heating network operates stably and the losses along the network are not considered, then under a uniform design temperature  $t_n$ , the heating design load  $Q_1$  of the building, the heat dissipation  $Q_2$  of the indoor radiators of the users, and the heat supply  $Q_3$  provided by the heating network to the heat users are equal. That is:

$$Q_1 = Q_2 = Q_3 \quad (1)$$

$Q_1$ ,  $Q_2$ , and  $Q_3$  satisfy the following relationships, respectively:

$$Q_1 = qv(t_n - t_w) \quad (2)$$

$$Q_2 = \alpha F \left( \frac{t_g + t_h}{2} - t_n \right)^{1+b} \quad (3)$$

$$Q_3 = Gc(t_g - t_h) / 3600 = 1.163G(t_g - t_h) \quad (4)$$

In the formula,  $Q_1$  — Design heat load of the building,  $W$ ,  $Q_2$  — Heat dissipation of the radiator,  $W$ ,  $Q_3$  — Heat supply of the heating network,  $W$ ,  $q$  — the volumetric heating heat index of the building,  $W / (m^3 \cdot ^\circ C)$ ,  $v$  — External volume of the building,  $m^3$ ,  $t_n$ ,  $t_w$  — Design indoor temperature and outdoor temperature,  $^\circ C$ ,  $\alpha$  — Heat transfer coefficient of the radiator under design conditions,  $W / (m^2 \cdot ^\circ C)$ ,  $F$  — Heat dissipation area of the radiator,  $m^2$ ,  $t_g$  and  $t_h$  — Supply water temperature and return water temperature of the heating network,  $^\circ C$ ,  $b$  — Correction factor for the radiator, generally taken as 0.3; when the indoor heating system is low-temperature radiant floor heating,  $b=0$ ,  $G$  — Design flow rate of the heating network,  $m^3 / h$ ,  $c$  — Specific heat capacity of water.

During operational adjustments, to facilitate research and calculations, the concepts of the ratio of relative heating load and the ratio of relative flow rate are introduced. That is, the ratio of actual heating load to design heating load and the ratio of actual flow rate to design flow rate.

$$\bar{Q} = \frac{Q_1}{Q'_1} = \frac{Q_2}{Q'_2} = \frac{Q_3}{Q'_3} \quad (5)$$

$$\bar{G} = \frac{G}{G'} \quad (6)$$

In practice, the volumetric heat index of a building is a complex parameter that is not only related to the outdoor temperature but also to factors such as outdoor wind speed, solar radiation intensity, and the orientation of the building. For the sake of convenience, the volumetric heat index of a building is treated as a constant value, so that the heating load is directly proportional to the temperature difference between the indoor and outdoor environments.

$$\bar{Q} = \frac{Q_1}{Q'_1} = \frac{t_n - t_w}{t'_n - t'_w} \quad (7)$$

Combining the above equations, we obtain:

$$\bar{Q} = \frac{t_n - t_w}{t'_n - t'_w} = \frac{(t_g + t_h - 2t_n)^{1+b}}{(t'_g + t'_h - 2t'_n)^{1+b}} = \bar{G} \frac{t_g - t_h}{t'_g - t'_h} \quad (8)$$

The above equation is the basic formula for operating adjustments in heating systems. When the outdoor temperature is at a certain value, to ensure that the indoor temperature remains constant, the ratio of supply and return water temperatures, the ratio of relative heat loads, and the ratio of relative flow rates should remain unchanged. The commonly used operating adjustment formulas in heating systems today are derived from this principle. In this paper, two main methods are employed: mass regulation and flow regulation.

### (1) Directly connected heating system

The operational adjustment methods for directly connected heating systems are relatively flexible, primarily involving mass regulation, flow regulation, staged variable flow mass regulation, and intermittent regulation operational formulas.

#### 1) Mass regulation

When a heating system uses mass regulation, since the network flow rate remains constant and only the supply and return water temperatures of the network are adjusted, the relative flow rate ratio is 1. That is:

$$\bar{G} = 1 \quad (9)$$

Substituting equation (9) into (8) yields the following expression for the supply and return water temperatures in the pipeline network:

$$\tau_1 = t_g = t_n + \Delta t'_s \bar{Q}^{\frac{1}{(1+b)}} + 0.5 \Delta t'_j \bar{Q} \quad (10)$$

$$\tau_2 = t_h = t_n + \Delta t'_s \bar{Q}^{\frac{1}{(1+b)}} - 0.5 \Delta t'_j \bar{Q} \quad (11)$$

In the equation:

$\Delta t'_s = 0.5(t'_g + t'_h - 2t_n)$  —Average temperature difference in user radiator design, °C;

$\Delta t'_j = t'_g - t'_h$  — Secondary network design supply and return water temperature difference, °C.

Based on the above equations (10) and (11), the mass regulation water temperature curves  $\tau_1 = f_1(\bar{Q})$ ,  $\tau_1 = f_1(t_w)$ ,  $\tau_2 = f_2(\bar{Q})$ , and  $\tau_2 = f_2(t_w)$  can be plotted.

#### 2) Volume regulation

During the operation of the heating system, the supply and return water temperatures of the pipeline network remain constant, and only the circulation flow rate of the pipeline network is changed. This type of regulation is called flow regulation.

The difference  $(t_g - t_h)$  in equation (8) remains constant, and the equation can be transformed as follows:

$$t_h = 2t_n + (t'_g + t'_h - 2t_n) \bar{Q}^{\frac{1}{(1+b)}} - t'_g \quad (12)$$

$$\bar{G} = \frac{t'_g - t'_h}{t_g - t_h} \bar{Q} \quad (13)$$

$$\bar{Q} = \frac{t_n - t_w}{t_n - t'_w} \quad (14)$$

#### 3) Stage-based flow rate adjustment

That is, use a smaller flow rate adjustment at the beginning and end of the heating season, and a larger flow rate adjustment during the middle of the heating season. Let the ratio of relative flow rates be a constant, that is:

$$\varphi = \bar{G} = \text{const} \quad (15)$$

Substituting equation (15) into (8) yields the supply return water temperature:

$$\tau_1 = t_g = t_n + \Delta t'_s \bar{Q}^{\frac{1}{(1+b)}} + 0.5 \frac{\Delta t'_j}{\varphi} \bar{Q} \quad (16)$$

$$\tau_2 = t_h = t_n + \Delta t'_s \bar{Q}^{\frac{1}{(1+b)}} - 0.5 \frac{\Delta t'_j}{\varphi} \bar{Q} \quad (17)$$

#### 4) Intermittent regulation

Intermittent regulation is generally used during the early and late stages of heating when outdoor temperatures are high. This regulation method does not require changes to the pipeline flow rate or supply and return water temperatures; it only requires a corresponding reduction in daily heating time based on changes in outdoor temperature. The specific formula is as follows:

$$T = 24 \frac{t_n - t_w}{t_n - t_w''} \quad (18)$$

In the formula,  $T$  — heating time,  $h/d$ ,  $t_w$  — outdoor temperature during the heating period,  $^{\circ}\text{C}$ ,  $t_w''$  — outdoor temperature when intermittent regulation begins,  $^{\circ}\text{C}$ .

## (2) Indirectly connected heating system

The heat network of an indirect heating system includes a primary network and a secondary network, which have relatively independent hydraulic conditions and can be regulated using different methods. The operating regulation formula for an indirect heating system requires supplementation to formula (8), namely:

$$\begin{aligned} \bar{Q} &= \frac{t_n - t_w}{t_n - t_w'} = \frac{(t_g + t_h - 2t_n)^{1+b}}{(t_g' + t_h' - 2t_n)^{1+b}} \\ &= \bar{G}_{cr} \frac{t_g - t_h}{t_g' - t_h'} = \bar{G}_{yj} \frac{\tau_1 - \tau_2}{\tau_1' - \tau_2'} \end{aligned} \quad (19)$$

In the equation,  $\bar{G}_{yj}$  and  $\bar{G}_{cr}$  — the ratio of relative flow rates on the primary and secondary sides,  $\tau_1$  and  $\tau_2$  — supply and return water temperatures on the primary side,  $^{\circ}\text{C}$ ,  $\tau_1'$  and  $\tau_2'$  — Primary side design supply and return water temperature,  $^{\circ}\text{C}$ .

The operational adjustment formulas for the secondary side of an indirect heating system can directly adopt the operational formulas for various adjustment methods in a direct connection system, while the primary side primarily employs mass adjustment or mass-flow adjustment. Based on the heat balance equation for heat release from a water-water heat exchanger, we obtain:

$$\bar{Q} = \bar{K} \frac{\Delta t}{\Delta t'} = \bar{G}_{yi}^{0.5} \bar{G}_{er}^{0.5} \frac{(\tau_1 - t_g) - (\tau_2 - t_h)}{\Delta t' \ln \left( \frac{\tau_1 - t_g}{\tau_2 - t_h} \right)} \quad (20)$$

where,  $\bar{K}$  — relative heat transfer coefficient ratio of the water-water heat exchanger. That is, when the outdoor temperature is  $t_w$ , the ratio of the actual heat transfer coefficient  $K$  to the design heat transfer coefficient  $K'$  (specifically, when mass regulation is used,  $\bar{K} = 1$ );

$\Delta t$  — Logarithmic mean temperature difference of the water-water heat exchanger when the outdoor temperature is  $t_w$ ,  $^{\circ}\text{C}$ ;

$\Delta t'$  — Design value of the logarithmic mean temperature difference of the water-water heat exchanger,  $^{\circ}\text{C}$ ;

$\Delta t'$  satisfies

$$\Delta t' = \frac{(\tau_1' - t_g') - (\tau_2' - t_h')}{\ln \left( \frac{\tau_1' - t_g'}{\tau_2' - t_h'} \right)} \quad (21)$$

In summary: Once the design values for each variable are determined, the actual supply and return water temperatures on the secondary side can be calculated using Equation (8) when the outdoor temperature is  $t_w$ . Then, the supply and return water temperatures on the primary side can be determined using Equations (19) and (20).

Indirectly connected heating systems generally adopt a combination of quality and quantity regulation, i.e., quantity regulation on the primary side and quality regulation on the secondary side. This ensures that the heating capacity of each heat exchanger station on the primary side tends to be uniform, the hydraulic conditions on the secondary side remain stable, and hydraulic imbalance in the pipeline network is reduced. The intelligent heating regulation system discussed in this paper only employs these two methods of quality and quantity regulation. During quality regulation, the climate compensator at the heat exchange station in this residential area can adopt different heating curves based on changes in outdoor temperature; during quantity regulation, the intelligent regulation system can adjust the circulation flow rate in the pipeline network by changing the power of the circulation pump.

### II. C. 3) Power consumption optimization model based on improved genetic algorithm

The energy-saving investments made in the early stages of constructing a nearly zero-energy building will affect its energy consumption in later stages. When constructing an optimization model for a nearly zero-energy building, it is assumed that the energy-saving technologies adopted in the early stages can achieve maximum effectiveness.

Let  $Z_1$  represent the incremental energy-saving benefits of the building and  $Z_2$  represent the cost of energy consumption. The objective function is determined with the goal of maximizing incremental benefits and minimizing energy costs. It is expressed as follows:

$$\max Z_1 = \sum_{i=1}^m \sum_{j=1}^n \Delta W_{ij} x_i x_{ij} (p_1 + \alpha \xi) P \Delta S \quad (22)$$

$$\min Z_2 = \sum_{i=1}^m \sum_{j=1}^n \Delta D_{ij} x_i x_{ij} \quad (23)$$

In the formula:  $\Delta W_g$  represents energy savings;  $i=1,2,3,\dots,m$  denotes the number of technology types used in the energy-saving scheme;  $j=1,2,3,\dots,n$  denotes the number of energy-saving schemes;  $x_i$  represents energy-saving technical measures;  $x_{ij}$  represents a specific energy-saving scheme;  $p_1$  is the electricity price at the building's location;  $\alpha$  is the energy conversion coefficient;  $\xi$  is the value of energy conservation and emission reduction;  $P$  is the discount factor;  $\Delta S$  is the incremental benefit of the target building each year;  $\Delta D_{ij}$  is the energy consumption cost under the  $j$ th energy-saving scheme of the  $i$ th technology.

Using an improved genetic algorithm with permutation encoding,  $x_{ij}$  is treated as a chromosome, which consists of multiple genes. The initial population is initialized, and the selection sorting method is used to calculate the fitness value of the chromosome. The formula is as follows:

$$E(y) = \kappa (1 - \kappa)^{i-1} \quad (24)$$

In the formula:  $\kappa$  is a random parameter. During the calculation process, determine the value of  $\kappa$ , and the value range of  $\kappa$  is 0~1. After completing the calculation of each chromosome fitness value, sort the results according to the calculation results until the chromosome number reaches the population size. Since there are two situations between energy-saving technologies, namely mutual exclusion and parallelism, during the calculation process, the energy-saving scheme  $x_{ij}$  can only take the value 1 in the chromosome fitness value sorting process.

Based on the fitness value of each chromosome, the reproduction probability of each chromosome is calculated to determine the size of its selection probability. The calculation formula is:

$$c_i = Z(x_{ij}) \left( \sum_{\varepsilon=1}^u Z_{\varepsilon} \right)^{-1} \quad (25)$$

In the equation:  $Z(x_{ij})$  is one of the solutions obtained by the objective function of chromosome  $y$ ;  $c_i$  is the reproduction probability of chromosome  $x_i$ ;  $u$  is the objective scalar of all chromosomes. A probability  $Z_{\varepsilon}$  is randomly generated from the reproduction probabilities of all chromosomes. The chromosome corresponding to this probability is selected as the parent chromosome. Crossover operations are performed on all chromosomes until offspring replacing the parent are generated, thereby obtaining a new population. The new population is solved to obtain the optimal result with the maximum incremental benefit and minimum energy cost, completing the construction of the power consumption optimization model.

## III. Research and testing of smart housing energy-saving systems based on Internet of Things technology

### III. A. Actual measurement and analysis of the system thermal environment

For residential buildings, residents typically spend most of their time in the living room during waking hours, with the exception of sleeping hours when they are in the bedroom. Therefore, it is necessary to conduct continuous testing of indoor temperature and humidity levels in both the bedroom and living room. The indoor temperature and humidity test data were obtained from on-site monitoring conducted from January 2023 to December 2024 in a certain residential community in a certain city. The temperature and humidity recorder sampled data every 10 minutes. The comparison sample included 15 smart homes equipped with an IoT temperature control system and 15 ordinary homes of the same type.



### III. A. 1) Indoor thermal environment during the cooling season

The indoor temperature distribution during the cooling season for smart housing and conventional housing is shown in Figure 3. As can be seen, the percentage distribution of indoor temperatures during the cooling season follows a normal distribution. Compared to smart housing, conventional housing has a slightly wider temperature distribution range and experiences more high-temperature weather. Among these, the percentage of indoor temperatures at 26°C during the cooling season is the highest for smart housing, accounting for 26.5%. The highest temperature is 30°C, the lowest temperature is 20°C, and the average temperature is 25°C. In conventional housing, the percentage of indoor temperatures at 28°C during the cooling season is the highest, accounting for 17.5%. The highest temperature is 35°C, the lowest temperature is 18°C, and the average temperature is 26.6°C. It can be seen that the indoor temperatures in smart housing during the cooling season are more comfortable.

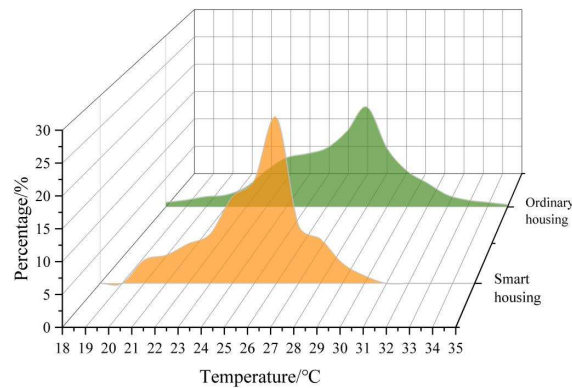


Figure 3: Indoor temperature distribution during the cooling season

The indoor humidity distribution during the cooling season for smart homes and conventional homes is shown in Figure 4. The relative humidity distribution ranges for smart homes and conventional homes during the cooling season are 30% to 70% and 20% to 100%, respectively. The relative humidity range for smart homes is slightly narrower than that for conventional homes. The IoT system significantly reduces the duration of excessive humidity by linking with fresh air dehumidification equipment.

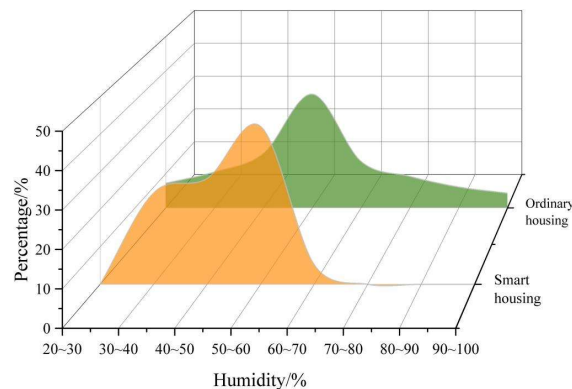


Figure 4: Distribution of indoor humidity during the cooling season

### III. A. 2) Indoor thermal environment during the heating season

The indoor temperature distribution during the heating season for smart homes and conventional homes is shown in Figure 5. Compared to smart homes, conventional homes have a slightly wider temperature distribution range and experience more high-temperature weather. Among these, the largest proportion of indoor temperatures in smart homes during the heating season is 25°C, accounting for 25.8%. The highest temperature is 27°C, and the lowest temperature is 18°C. The largest proportion of indoor temperatures in conventional homes during the heating season is 20°C, accounting for 24.3%. The highest temperature is 24°C, and the lowest temperature is 10°C. It is evident that smart housing is more comfortable during the heating season than conventional housing.



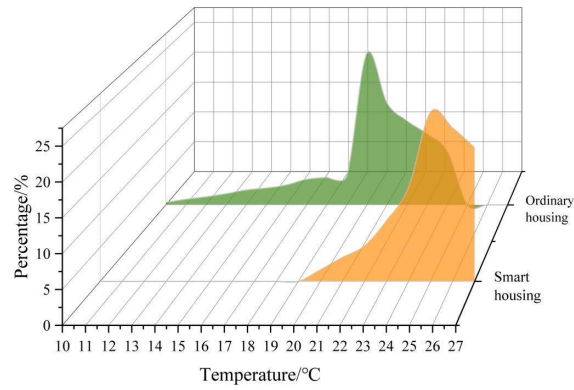


Figure 5: Indoor temperature distribution during the heating season

The distribution of indoor relative humidity during the heating season for smart homes and conventional homes is shown in Figure 6, with both distributions ranging from 30% to 90%. The relative humidity in smart homes exhibits a single-peak distribution, with the peak occurring in the 50–60% range, accounting for 42.2% of the data. 73.6% of the data is concentrated within the 50–70% comfort range, indicating that the IoT humidity control system can effectively maintain a stable state. In contrast, the humidity distribution in conventional homes shows a significant right skew, with periods where humidity exceeds 70% accounting for 27.8% of the data, which can easily lead to condensation.

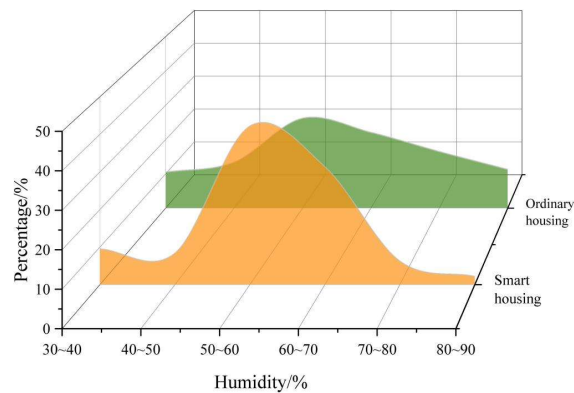


Figure 6: Distribution of indoor relative humidity during the heating season

### III. B. Energy consumption characteristics analysis

#### III. B. 1) Total energy consumption

Data on total energy consumption was collected based on monthly electricity consumption. Figure 7 shows the monthly distribution of total energy consumption in 2023. Energy consumption was high in January and December, which were the peak periods for energy consumption in 2023.

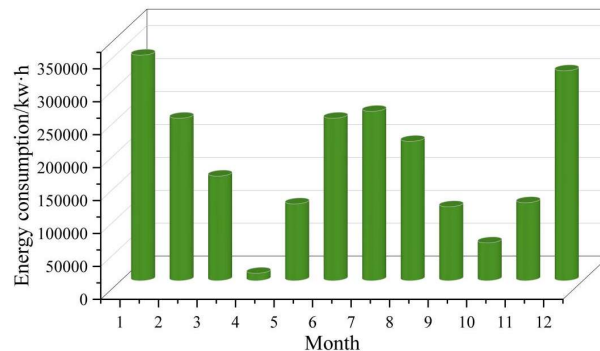


Figure 7: Monthly distribution of total energy consumption in 2023

The monthly distribution of total energy consumption in 2024 is shown in Figure 8. Energy consumption is high in January, February, July, August, and December, which are the peak periods for energy consumption in 2024. Energy consumption is low in April and October, which are the trough periods for energy consumption in 2024.

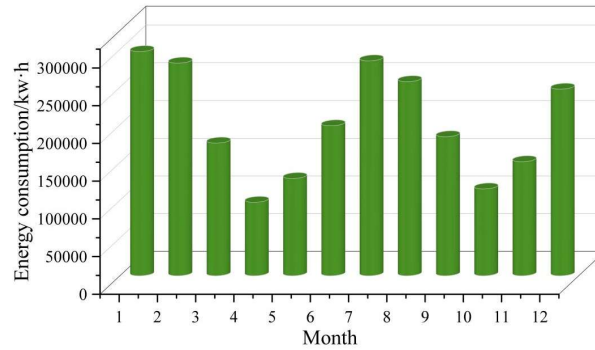
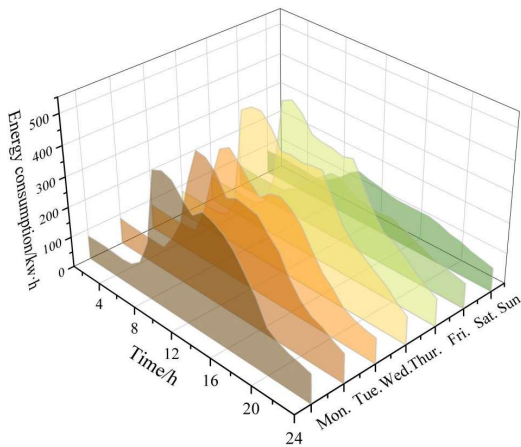


Figure 8: Monthly distribution of total energy consumption in 2024

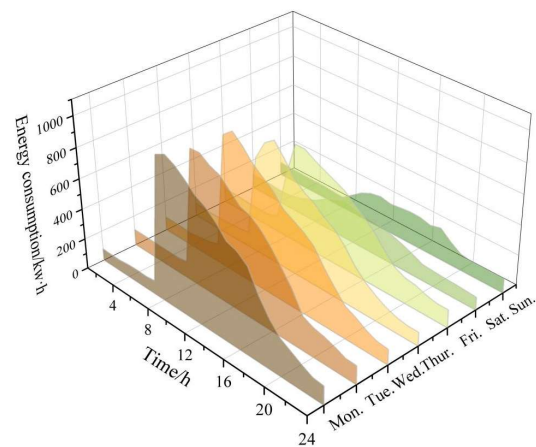
The patterns of energy consumption changes between 2023 and 2024 are relatively consistent. Energy consumption exhibits both peak and off-peak periods throughout the year. Peak periods typically occur in December, January, February, June, July, and August, with energy consumption in December, January, and February being similar, and that in June, July, and August also being similar. The low points occur in March, April, May, September, October, and November. The primary reason for this is that energy consumption varies with the seasons. During winter and summer, energy consumption may reach its peak due to increased heating and cooling demands. In contrast, during spring and autumn, when the climate is more moderate, energy consumption may be relatively lower.

### III. B. 2) Sub-item energy consumption

Taking a specific weekday in January 2024 as an example, the hourly distribution results of energy consumption by category and item are shown in Figure 9 (a–d). Energy consumption for each category and item is higher during working hours each day, with peak consumption occurring between 9:00 a.m. and 5:00 p.m. Energy consumption is lower during non-working hours each day, with off-peak consumption occurring between 5:00 p.m. and 9:00 a.m. the following day.



(a) Light



(b) Air conditioner

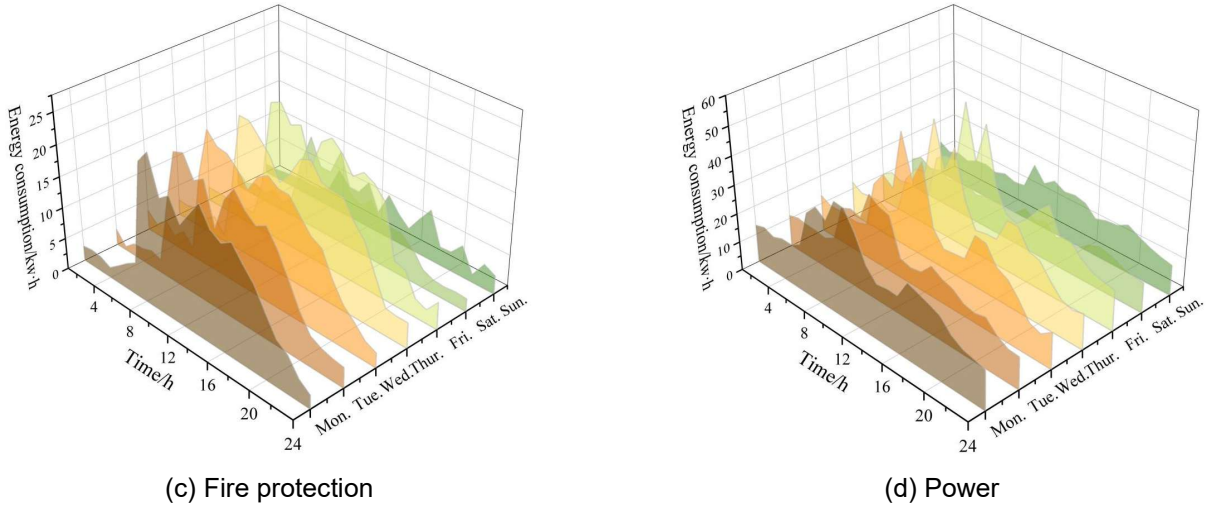


Figure 9: Distribution of energy consumption per hour by category and subitem

### III. B. 3) Building Energy Consumption

The smart residential building consists of 7 floors. To investigate the energy consumption distribution across different floors, statistical analysis was conducted on energy consumption data from each floor. The monthly energy consumption distribution is shown in Figure 10. The monthly energy consumption patterns across different floors are similar, with summer and winter being peak consumption periods and spring and autumn being low consumption periods. By analyzing the monthly energy consumption distribution across different floors, it can be observed that the total energy consumption is higher on floors 1 and 5, while it is lower on floors 3 and 7.

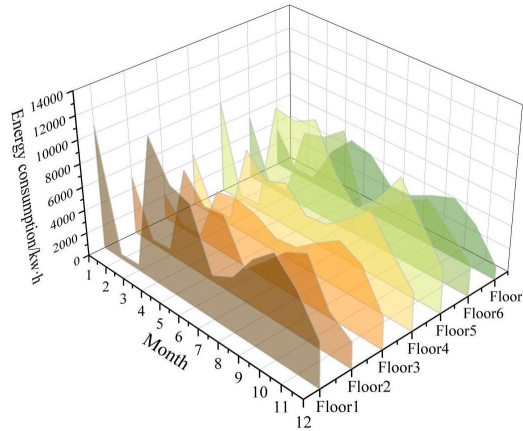


Figure 10: Monthly energy consumption distribution

### III. C. Analysis of the Effectiveness of the Power Consumption Optimization Model

When analyzing the effectiveness of an intelligent housing power consumption optimization model, the first step is to start with each energy-saving system to develop different energy-saving schemes. Based on these schemes, the model is used to determine the optimal combination of solutions. The improved genetic algorithm proposed in this paper is employed to analyze the trend in energy-saving design efficiency. The trend in energy-saving design efficiency as a function of the benchmark yield rate is shown in Figure 11. In the model under study, the benchmark yield rate serves as a critical reference indicator, exerting a significant influence on the objective function. Energy-saving benefits decrease as the proportion of factors increases, dropping from 4,629.52 yuan/m<sup>2</sup> at 3% to 2,023.47 yuan/m<sup>2</sup> at 13%, indicating that the economic benefits of reducing energy consumption diminish as the energy-saving proportion increases. When the benchmark yield rate is 10%, the energy-saving design efficiency reaches its maximum value of 13.35%, which is lower than the 22.85% at 3%. This indicates that better energy-saving benefits can be achieved when investment costs are relatively low. However, when the factor ratio increases to 13%,

the energy-saving design efficiency decreases to 10.45%, meaning that the energy-saving benefits per unit of investment are reduced.

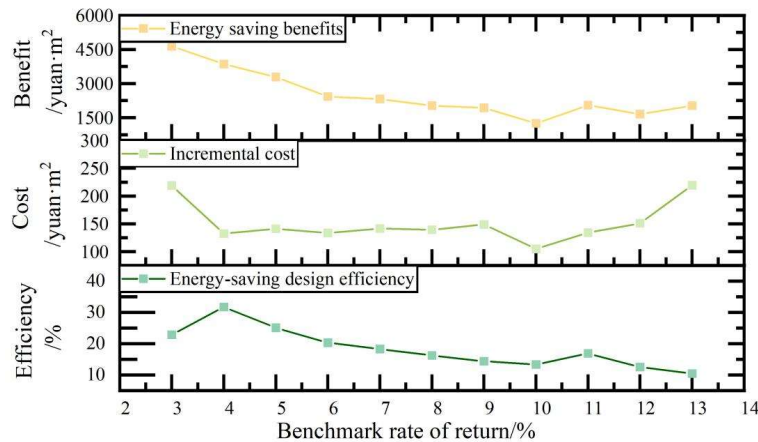


Figure 11: The change trend of energy-saving design efficiency with benchmark yield

#### IV. Conclusion

This paper designs an IoT-based smart housing energy-saving system that achieves intelligent control of the residential environment and efficient energy management through a three-layer architecture.

During the cooling season, indoor temperatures are normally distributed. Compared to smart housing, ordinary housing has a slightly wider temperature distribution range and more hot weather. In smart housing, the largest proportion of indoor temperatures during the cooling season is 26°C, accounting for 26.5%. In conventional housing, the largest percentage of indoor temperatures during the cooling season is 28°C, accounting for 17.5%. The relative humidity range in smart housing is slightly narrower than that in conventional housing. The IoT system reduces the duration of excessive humidity by coordinating with fresh air dehumidification equipment. In smart housing, the largest percentage of indoor temperatures during the heating season is 25°C, accounting for 25.8%. In conventional housing, the largest percentage of indoor temperatures during the heating season is 20°C, accounting for 24.3%. The relative humidity data for smart housing at 73.6% is concentrated within the 50-70% comfort range, while the proportion of time when humidity exceeds 70% in ordinary housing reaches 27.8%, which can easily lead to condensation.

Energy consumption in smart housing exhibits peak and off-peak periods throughout the year. Peak periods generally occur in December, January, February, June, July, and August, with similar energy consumption levels in December, January, and February, and June, July, and August. Off-peak periods occur in March, April, May, September, October, and November. Energy consumption for each category and subcategory is higher during working hours each day, with peak consumption occurring between 9:00 AM and 5:00 PM. Energy consumption is lower during non-working hours each day, with off-peak consumption occurring between 5:00 PM and 9:00 AM the following day. Floors 1 and 5 have higher total energy consumption, while floors 3 and 7 have lower total energy consumption.

Energy-saving benefits decrease as the proportion of factors increases, from 3% at 4,629.52 yuan/m² to 13% at 2,023.47 yuan/m², indicating that the economic benefits of reducing energy consumption decrease as the energy-saving proportion increases.

#### References

- [1] Elkholy, M. H., Senjyu, T., Lotfy, M. E., Elgarhy, A., Ali, N. S., & Gaafar, T. S. (2022). Design and implementation of a real-time smart home management system considering energy saving. *Sustainability*, 14(21), 13840.
- [2] Machorro-Cano, I., Alor-Hernández, G., Paredes-Valverde, M. A., Rodríguez-Mazahua, L., Sánchez-Cervantes, J. L., & Olmedo-Aguirre, J. O. (2020). HEMS-IoT: A big data and machine learning-based smart home system for energy saving. *Energies*, 13(5), 1097.
- [3] Jnat, K., Shahrour, I., & Zaoui, A. (2020). Impact of smart monitoring on energy savings in a social housing residence. *Buildings*, 10(2), 21.
- [4] Tomal, M. (2020). Moving towards a smarter housing market: The example of Poland. *Sustainability*, 12(2), 683.
- [5] Colistra, J. (2019). Innovations in housing for smart cities. *Journal of Architectural Engineering*, 25(4), 06019001.
- [6] Hildayanti, A., & Machrizandi, M. S. R. (2020). The application of iot (internet of things) for smart housing environments and integrated ecosystems. *Nature: National Academic Journal of Architecture*, 7(1), 80-88.
- [7] Wen, S., & Liu, H. (2022). Research on energy conservation and carbon emission reduction effects and mechanism: Quasi-experimental evidence from China. *Energy Policy*, 169, 113180.

- [8] Xu, T., Kang, C., & Zhang, H. (2022). China's efforts towards carbon neutrality: does energy-saving and emission-reduction policy mitigate carbon emissions?. *Journal of Environmental Management*, 316, 115286.
- [9] Ahmad, H. B., Asaad, R. R., Almufti, S. M., Hani, A. A., Sallow, A. B., & Zeebaree, S. R. (2024). Smart home energy saving with big data and machine learning. *Jurnal Ilmiah Ilmu Terapan Universitas Jambi*, 8(1), 11-20.
- [10] Paredes-Valverde, M. A., Alor-Hernández, G., García-Alcaráz, J. L., Salas-Zárate, M. D. P., Colombo-Mendoza, L. O., & Sánchez-Cervantes, J. L. (2020). IntelliHome: An internet of things-based system for electrical energy saving in smart home environment. *Computational Intelligence*, 36(1), 203-224.
- [11] Pohl, J., Frick, V., Hoefner, A., Santarius, T., & Finkbeiner, M. (2021). Environmental saving potentials of a smart home system from a life cycle perspective: How green is the smart home?. *Journal of Cleaner Production*, 312, 127845.
- [12] Cottone, P., Gaglio, S., Re, G. L., & Ortolani, M. (2015). User activity recognition for energy saving in smart homes. *Pervasive and Mobile Computing*, 16, 156-170.
- [13] Bhati, A., Hansen, M., & Chan, C. M. (2017). Energy conservation through smart homes in a smart city: A lesson for Singapore households. *Energy Policy*, 104, 230-239.
- [14] Lima, W. S., Souto, E., Rocha, T., Pazzi, R. W., & Pramudianto, F. (2015, July). User activity recognition for energy saving in smart home environment. In *2015 IEEE symposium on computers and communication (ISCC)* (pp. 751-757). IEEE.
- [15] Soheilian, M., Fischl, G., & Aries, M. (2021). Smart lighting application for energy saving and user well-being in the residential environment. *Sustainability*, 13(11), 6198.
- [16] Taiwo, O., & Ezugwu, A. E. (2021). Internet of things-based intelligent smart home control system. *Security and Communication Networks*, 2021(1), 9928254.
- [17] Stojkoska, B. L. R., & Trivodaliev, K. V. (2017). A review of Internet of Things for smart home: Challenges and solutions. *Journal of cleaner production*, 140, 1454-1464.
- [18] Albany, M., Alsaifi, E., Alruwili, I., & Elkhediri, S. (2022). A review: secure internet of thing system for smart houses. *Procedia Computer Science*, 201, 437-444.
- [19] Rock, L. Y., Tajudeen, F. P., & Chung, Y. W. (2024). Usage and impact of the internet-of-things-based smart home technology: a quality-of-life perspective. *Universal access in the information society*, 23(1), 345-364.
- [20] Alaa, M., Zaidan, A. A., Zaidan, B. B., Talal, M., & Kiah, M. L. M. (2017). A review of smart home applications based on Internet of Things. *Journal of network and computer applications*, 97, 48-65.
- [21] Elmalaki, S., Shoukry, Y., & Srivastava, M. (2018, November). Internet of personalized and autonomous things (iopat) smart homes case study. In *Proceedings of the 1st ACM International Workshop on Smart Cities and Fog Computing* (pp. 35-40).
- [22] Krishnan, P., Prabu, A. V., Loganathan, S., Routray, S., Ghosh, U., & AL-Numay, M. (2023). Analyzing and managing various energy-related environmental factors for providing personalized IoT services for smart buildings in smart environment. *Sustainability*, 15(8), 6548.