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IOT-BASED NETWORK ARCHITECTURE FOR INTELLIGENT RESIDENTIAL ENERGY-SAVING SYSTEMS

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This study presents a network architecture for an intelligent residential energy-saving system built on Internet of Things (IoT) technology. The sensing layer is implemented using ZigBee, while remote supervision and control are enabled through Internet connectivity and GPRS. The proposed system integrates multiple functions, including home security, smart regulation of lighting and indoor temperature, household-level heat metering, and electricity-use monitoring. To improve energy performance, an electricity-consumption optimization model is developed using an enhanced genetic algorithm. Field experiments and data analysis confirm the system's effectiveness in regulating indoor thermal conditions and optimizing energy use. In the cooling season, smart housing most frequently maintains an indoor temperature of 26°C (26.5% of observations), whereas conventional housing most often records 28°C (17.5%). Smart housing also exhibits a slightly narrower indoor relative-humidity range. During the heating season, thermal comfort in smart housing remains notably better than in conventional residences, and the IoT system significantly shortens periods when humidity exceeds acceptable limits. Economic analysis further indicates diminishing returns: as the targeted energy-saving proportion rises, the incremental economic benefit of reducing consumption declines—moving from about 3% at 4,629.52 yuan/m² to about 13% at 2,023.47 yuan/m²—suggesting that higher energy-saving targets may yield smaller marginal financial gains.

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

INTRODUCTION

In the internet-driven era, smart home energy-saving systems have become a key technical pillar for advancing energy efficiency and pollution reduction. Their rapid growth is closely tied to the evolution of smart housing technologies and the rising public emphasis on conserving energy and cutting emissions [1, 2, 3]. Smart housing itself can be viewed as an outcome of the information age, shaped by breakthroughs in intelligent technologies, broader social development, and people's increasingly diverse and continually upgrading living requirements [4, 5, 6]. In China, the elevation of "energy conservation and emissions reduction" as a major national goal during the 11th Five-Year Plan further strengthened public awareness and accelerated related initiatives across the country [7, 8].

Energy-saving systems for smart housing built on IoT technologies connect household appliances and devices to the internet, enabling seamless interconnection and supporting more convenient and intelligent daily living [9, 10, 11]. From an energy management perspective, IoT-enabled systems can track and regulate residential electricity consumption using smart meters, smart sockets, and similar components, guiding users toward more efficient energy use and minimizing unnecessary waste [12, 13, 14]. Beyond conservation benefits, IoT-based smart home energy-saving systems also offer clear functional advantages over traditional appliances [15]. One major benefit is remote control and real-time monitoring: users can operate and supervise home devices through mobile terminals regardless of time or location, removing the limitations of on-site access [16, 17]. Another strength is device-level interoperability, which improves coordination among appliances, supports automated operation, and enables more advanced household workflows [18, 19, 20]. Moreover, by incorporating big data analytics and artificial intelligence, such systems can deliver customized intelligent services that adapt to user behavior patterns and household preferences [21, 22].

This study begins by introducing a multi-layer system architecture composed of a perception layer, a network layer, and an application layer. ZigBee is employed to support flexible networking, while embedded gateways are adopted in place of conventional servers to lower deployment costs. The work then explains in detail how data are collected and how device linkage is implemented using temperature, humidity, and illumination sensors, and it integrates household heat metering to enable community-scale energy-saving regulation. For monitoring building electricity consumption, a sub-metering strategy is proposed, and an improved genetic algorithm is used to formulate an optimization model. Finally, field experiments compare the thermal environment of smart housing with that of standard housing to demonstrate the advantages of smart housing, and overall energy consumption is evaluated to confirm the effectiveness of the proposed optimization model.

DESIGN OF AN INTELLIGENT HOUSING ENERGY-SAVING SYSTEM BASED ON INTERNET OF THINGS TECHNOLOGY

With the fast-paced growth of IoT technologies, smart housing solutions are increasingly capable of enhancing residential comfort while also improving energy performance. This study centers on the design of an IoT-enabled smart housing energy-saving system, aiming to overcome common weaknesses of conventional residences in areas such as energy-use oversight and indoor environment regulation.

Overall Design of Smart Housing Energy-Saving Systems

The research object is an intelligent, energy-efficient residential building system. For smart functionality, the proposed design adopts ZigBee for indoor networking, since its flexible topology and suitability for household scenarios make it a practical choice. Connectivity beyond the home is implemented through two channels:

Internet access and GPRS. In this way, residents can supervise and manage the building via smart terminal devices. To perform protocol translation among these three networks, the system employs an embedded gateway rather than a traditional PC-based server, which improves operational reliability, reduces physical footprint, and lowers both energy demand and deployment cost. This architecture supports key functions including residential security, smart lighting regulation, intelligent temperature adjustment, and automated alarm services. From the perspective of energy conservation, the system integrates an individual heat metering solution for residential heating, enabling community-wide energy-saving regulation. At the same time, an intelligent monitoring platform for household equipment provides itemized electricity metering and helps reduce standby power consumption.

Overall, the smart and energy-efficient residential system is organized into three layers: the perception layer, the network layer, and the application layer.

Building the system perception layer based on ZigBee technology

The lighting and automatic temperature control subsystem is designed to acquire indoor illumination and temperature information, then regulate lighting brightness and curtain operation to achieve suitable visual conditions. In parallel, it coordinates household heat metering devices and air-conditioning equipment so that indoor temperature remains comfortable and stable.

At the sensing layer, subsystem nodes are composed of temperature–humidity sensors, light sensors, relays, infrared transmission modules, and ZigBee communication modules. These nodes capture indoor light intensity and temperature/humidity readings and forward them to an embedded web server for analysis. After processing, the server returns control commands that adjust appliances and regulate heating water valves. In terms of operating logic, this subsystem follows the same general mechanism as the health monitoring subsystem and the remote-control subsystem for information appliances.

In addition, the subsystem incorporates residential heat metering, where each household acts as an independent unit and the scheme can be extended to an entire building or even a full community. Each home is equipped with a dedicated heat meter, typically installed at the household entry point to measure thermal energy usage. Using the self-regulating and automatic adjustment capability of thermostatic valves mounted on radiators, the hot-water flow through the radiators can be varied. This leads to variable-flow operation on the load side of the heating system within the household heat-metering framework.

IoT-based building power consumption monitoring

Overall Design

IoT-enabled power consumption monitoring in buildings must capture electricity-use data without disrupting the normal operation of devices. To meet this requirement, a building power monitoring system is designed with three core modules: an information acquisition terminal, a network communication terminal, and a centralized management unit.

The information acquisition terminal relies on ZigBee to track the real-time operating status of on-site equipment. The network communication module gathers device status information, forwards it for processing, and extracts operational parameters—including runtime, current, voltage, and power—from each monitored device. These data are then transmitted to the centralized management unit, where they are analyzed and processed to estimate the overall energy consumption of each device and the building as a whole. Finally, the processed energy-use results are delivered to the energy management system to support energy-saving decisions and control actions. The structure of the information collector is shown in Figure 1.

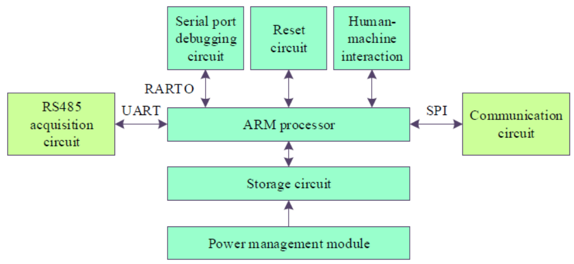

Figure 1: Structure of information collector.

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.

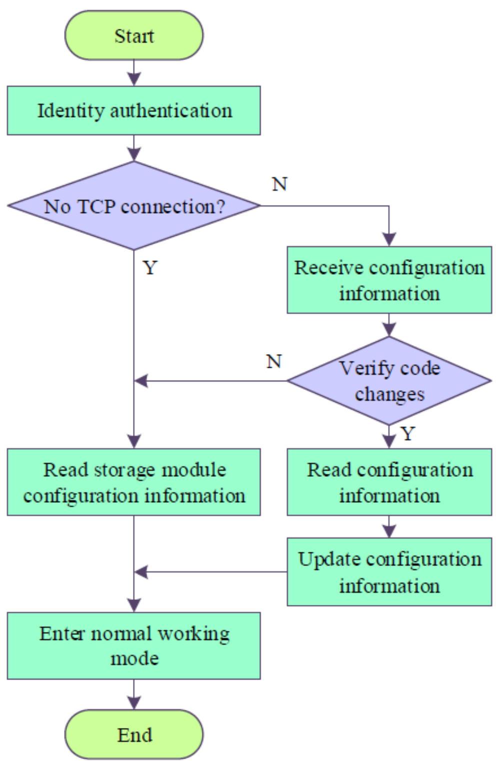

Figure 2: Schematic of self configuration process of collector.

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.

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:

$$Q_1 = Q_2 = Q_3. \tag{1}$$

Q_1, Q_2, and Q_3 satisfy:

$$Q_1 = qv\left(t_n - t_w\right), \tag{2}$$

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

$$Q_3 = \frac{Gc\left(t_g - t_h\right)}{3600} = 1.163\,G\left(t_g - t_h\right). \tag{4}$$

In the formula, Q_1 is building design heat load (W), Q_2 radiator heat dissipation (W), Q_3 network heat supply (W), q is volumetric heating index (W/(m^3·°C)), v is external volume (m^3), t_n, t_w are design indoor/outdoor temps (°C), α is radiator heat transfer coefficient, F radiator area (m^2), t_g, t_h supply/return water temperatures (°C), b correction factor (typically 0.3; for low-temp radiant floor heating $b = 0$), G design flow rate (m^3/h), c specific heat.

Define relative heating load ratio and relative flow ratio:

$$Q' = \frac{Q_1}{Q_1'} = \frac{Q_2}{Q_2'} = \frac{Q_3}{Q_3'}, \tag{5}$$

$$G' = \frac{G}{G'}. \tag{6}$$

Treating the volumetric heat index as constant gives:

$$Q' = \frac{t_n - t_w}{t_n - t_w'}, \tag{7}$$

and combining yields the basic operating adjustment formula:

$$Q' = G' = \frac{\left(\frac{t_g + t_h}{2} - t_n\right)^{1+b}\left(t_g - t_h\right)}{\left(\frac{t_g' + t_h'}{2} - t_n\right)^{1+b}\left(t_g' - t_h'\right)}. \tag{8}$$

This is the basis for common heating regulation formulas. This paper uses mass regulation and flow regulation.

(1) Directly connected heating system **1) Mass regulation.** When flow is constant, the relative flow ratio is:

$$G' = 1. \tag{9}$$

Substitute into (8) to get supply/return temperature formulas (secondary network):

$$t_g = t_n + \Delta t_s + Q'^{\frac{1}{1+b}} \Delta t_j, \tag{10}$$

$$t_h = t_n + \Delta t_s - Q'^{\frac{1}{1+b}} \Delta t_j, \tag{11}$$

where $\Delta t_s = \left(\frac{t'_g + t'_h}{2} - t_n\right)$ and $\Delta t_j = t'_g - t'_h$.

2) Flow regulation. Keep $(t_g - t_h)$ constant and vary the circulation flow:

$$t_h = t_n + \left(\frac{t_g + t_h}{2} - t_n\right)^{1+b} Q', \tag{12}$$

$$G' = Q' \frac{t'_g - t'_h}{t_g - t_h}, \tag{13}$$

$$Q' = \frac{t_n - t_w}{t_n - t'_w}. \tag{14}$$

3) Stage-based flow rate adjustment. Let:

$$\varphi = G' = \text{const.} \tag{15}$$

Then:

$$t_g = t_n + \Delta t_s + \frac{Q'^{\frac{1}{1+b}} \Delta t_j}{\varphi}, \tag{16}$$

$$t_h = t_n + \Delta t_s - \frac{Q'^{\frac{1}{1+b}} \Delta t_j}{\varphi}. \tag{17}$$

4) Intermittent regulation. Reduce daily heating time:

$$T = 24 \frac{t_n - t_w}{t_n - t''_w}, \tag{18}$$

where T is heating time (h/day), t_w outdoor temperature during heating, and t''_w outdoor temperature when intermittent regulation begins.

(2) Indirectly connected heating system For indirect systems (primary + secondary networks), the operating adjustment formula is supplemented:

$$Q' = \frac{\left(\frac{t_g + t_h}{2} - t_n\right)^{1+b} (t_g - t_h)}{\left(\frac{t'_g + t'_h}{2} - t_n\right)^{1+b} (t'_g - t'_h)} = G'_{yi} = G'_{er}. \tag{19}$$

Here G'_{yi}, G'_{er} are relative flow ratios on primary/secondary sides, and τ_1, τ_2 denote primary supply/return water temperatures.

Using the heat balance of a water-water heat exchanger:

$$Q' = K\,G'_{yi}\,G'_{er}\,\frac{\Delta t}{\Delta t'}, \tag{20}$$

where K is relative heat transfer coefficient ratio, Δt is log-mean temperature difference, and $\Delta t'$ is design log-mean difference:

$$\Delta t' = \frac{(t'_g - t'_h) - (\tau'_1 - \tau'_2)}{\ln\left(\frac{t'_g-\tau'_1}{t'_h-\tau'_2}\right)}. \tag{21}$$

The secondary side can use the direct-system formulas, while the primary side mainly uses mass or mass-flow regulation. This paper uses a combination of quantity regulation on the primary side and quality regulation on the secondary side.

Power consumption optimization model based on improved genetic algorithm

Early-stage energy-saving investments affect later-stage energy consumption in near-zero-energy buildings. Let Z_1 be incremental energy-saving benefits and Z_2 be energy consumption costs. The dual objective is:

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

$$\min Z_2 = \sum_{i=1}^{m}\sum_{j=1}^{n} \Delta D_{ij}\,x_i\,x_{ij}. \tag{23}$$

Here ΔW_{ij} is energy savings; $i = 1,\dots,m$ is technology type; $j = 1,\dots,n$ is scheme index; x_i is technical measure; x_{ij} is specific scheme; p_1 is electricity price; α conversion coefficient; ξ value of energy conservation/emission reduction; P discount factor; ΔS yearly incremental benefit; ΔD_{ij} energy cost under scheme j of technology i.

Using an improved GA with permutation encoding, treat x_{ij} as a chromosome of genes. Fitness is computed by:

$$E(y) = 1 - \kappa^{-1}, \tag{24}$$

where $\kappa \in [0,1]$ is random (as described in the paper).

The reproduction probability is:

$$c_i = \frac{Z(x_{ij})}{\sum_{\varepsilon=1}^{u} Z_\varepsilon}, \tag{25}$$

where $Z(x_{ij})$ is one objective scalar solution from chromosome y, u is the number of objective scalars. A random probability Z_ε is generated to select a parent chromosome. Crossover is performed to generate offspring replacing parents, forming a new population. The new population is solved to obtain the optimal result maximizing incremental benefit and minimizing energy cost.

RESEARCH AND TESTING OF SMART HOUSING ENERGY-SAVING SYSTEMS BASED ON INTERNET OF THINGS TECHNOLOGY

Actual measurement and analysis of the system thermal environment

Residents spend most waking time in living rooms and sleeping time in bedrooms, so continuous temperature/humidity testing is performed in both. Data comes from on-site monitoring from January 2023 to December 2024 in a residential community. Sampling every 10 minutes. 15 smart homes (with IoT temperature control) and 15 ordinary homes are compared.

Indoor thermal environment during the cooling season

Figure 3 shows indoor temperature distribution during cooling season. Compared to smart housing, conventional housing has a wider temperature range and more high-temperature periods. Smart housing peaks at 26°C (26.5%); highest 30°C, lowest 20°C, mean 25°C. Conventional housing peaks at 28°C (17.5%); highest 35°C, lowest 18°C, mean 26.6°C.

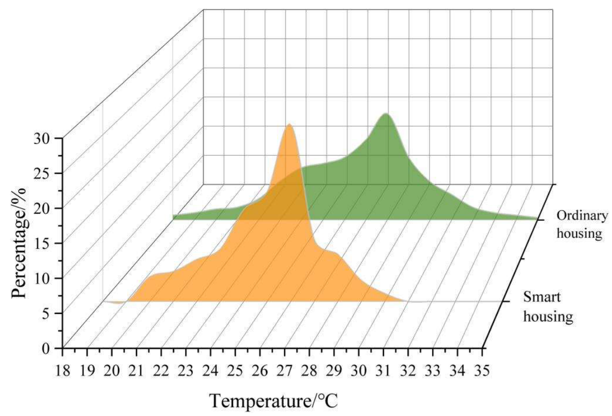

Figure 3: Indoor temperature distribution during the cooling season.

Figure 4 shows humidity distribution. Smart housing ranges 30%–70%, conventional 20%–100%. The IoT system reduces excessive humidity duration by linking fresh-air dehumidification equipment.

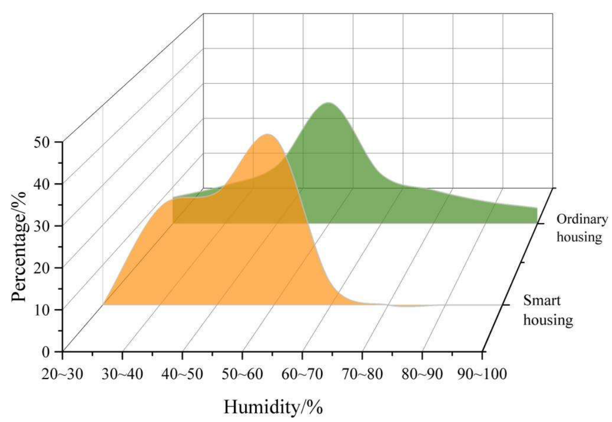

Figure 4: Distribution of indoor humidity during the cooling season.

Indoor thermal environment during the heating season

Figure 5 shows temperature distribution during heating season. Smart housing peaks at 25°C (25.8%); highest 27°C, lowest 18°C. Conventional peaks at 20°C (24.3%); highest 24°C, lowest 10°C.

Figure 6 shows humidity distribution during heating season. Both range 30%–90%. Smart housing has a

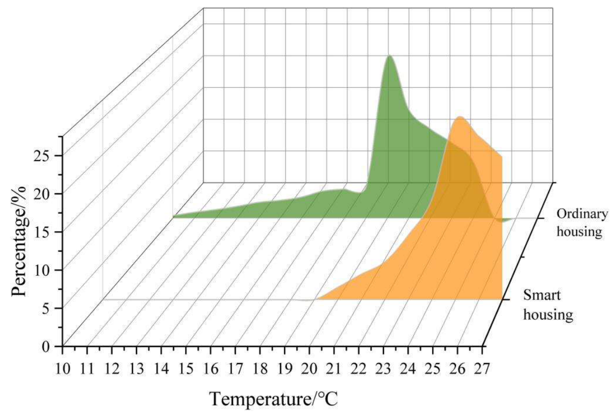

Figure 5: Indoor temperature distribution during the heating season.

single peak at 50–60% (42.2%); 73.6% within 50–70% comfort. Conventional shows right skew; humidity >70% accounts for 27.8%.

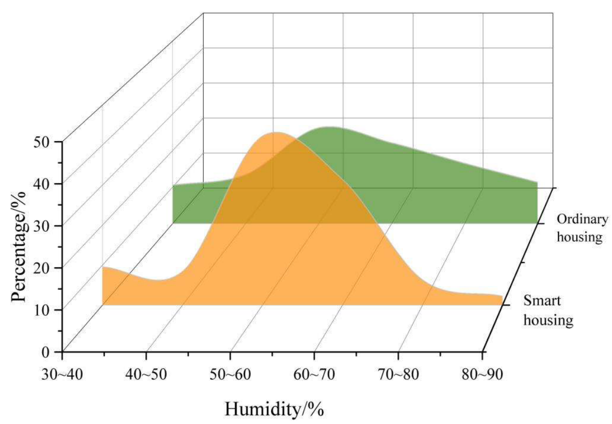

Figure 6: Distribution of indoor relative humidity during the heating season.

Energy consumption characteristics analysis

Total energy consumption

Monthly total energy consumption in 2023 is shown in Figure 7. January and December are peak periods.

Monthly total energy consumption in 2024 is shown in Figure 8. Peaks occur in January, February, July, August, and December; troughs in April and October.

Energy consumption peaks in winter and summer due to heating/cooling loads, and is lower in spring/autumn.

Sub-item energy consumption

Taking a weekday in January 2024, hourly distributions by category and item are shown in Figure 9. Energy consumption is higher during working hours (9:00–17:00) and lower during non-working hours (17:00–9:00 next day).

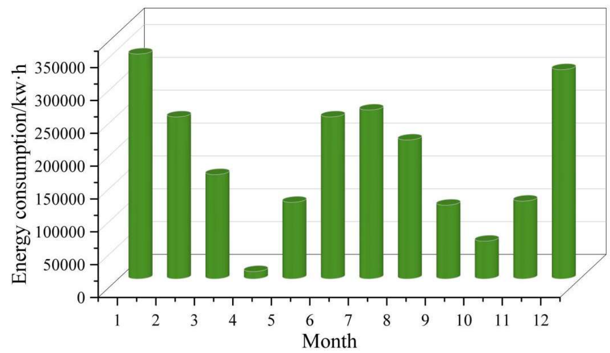

Figure 7: Monthly distribution of total energy consumption in 2023.

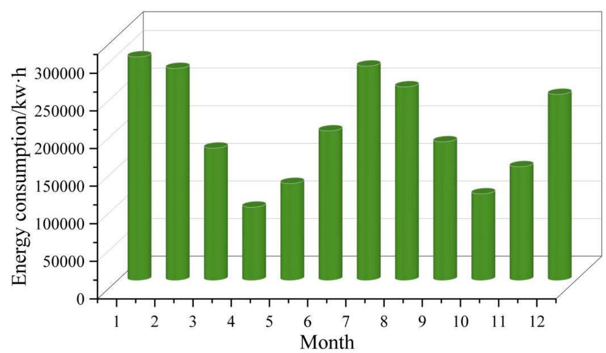

Figure 8: Monthly distribution of total energy consumption in 2024.

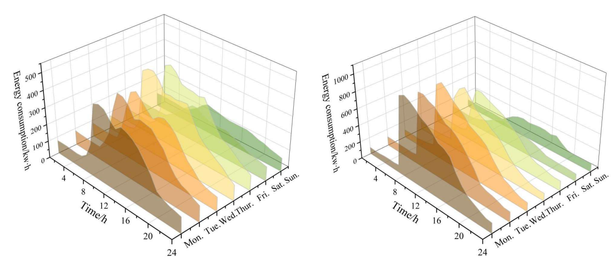

Figure 9: Distribution of energy consumption per hour by category and subitem.

Building Energy Consumption

The smart residential building has 7 floors. Monthly energy consumption distribution is shown in Figure 10. Patterns are similar across floors (summer/winter peaks; spring/autumn lows). Total energy consumption is higher on floors 1 and 5, lower on floors 3 and 7.

Analysis of the Effectiveness of the Power Consumption Optimization Model

Different energy-saving schemes are constructed from each system; the model determines the optimal combination. The improved GA is used to analyze trends in energy-saving design efficiency. The trend versus benchmark yield rate is shown in Figure 11. Energy-saving benefits decrease as factor proportion increases, from 4,629.52 yuan/m^2 at 3% to 2,023.47 yuan/m^2 at 13%, implying diminishing economic returns as energy-saving proportion increases. When benchmark yield rate is 10%, energy-saving design efficiency

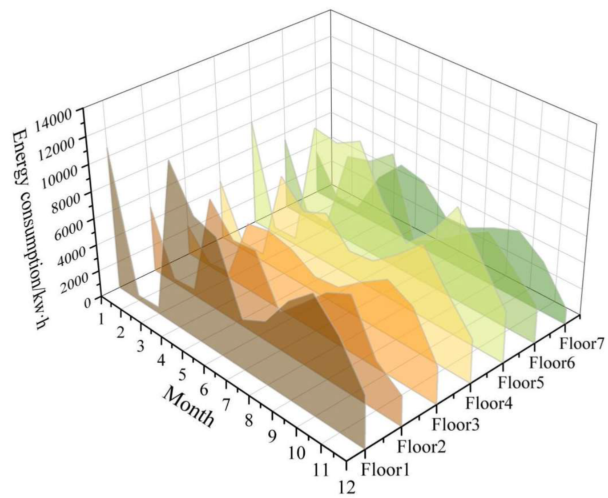

Figure 10: Monthly energy consumption distribution.

reaches 13.35% (lower than 22.85% at 3%); when factor ratio rises to 13%, efficiency decreases to 10.45%.

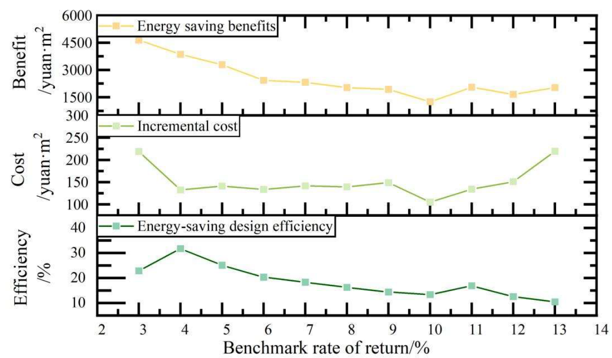

Figure 11: The change trend of energy-saving design efficiency with benchmark yield.

CONCLUSION

This study presents an IoT-enabled smart housing energy-saving system that supports intelligent indoor environment regulation and effective energy management through a three-layer architectural design.

During the cooling season, indoor temperature readings follow an approximately normal distribution. Compared with smart housing, conventional housing shows a slightly broader temperature spread and a higher occurrence of hotter conditions. In smart housing, the most frequent indoor temperature in the cooling season is 26°C, representing 26.5% of observations. By contrast, in ordinary housing, the highest share occurs at 28°C, accounting for 17.5%. The relative humidity range in smart housing is also somewhat tighter than in conventional housing, and the IoT system shortens the duration of overly humid conditions by coordinating operation with fresh-air dehumidification equipment.

During the heating season, smart housing most commonly maintains an indoor temperature of 25°C, which accounts for 25.8% of the measured distribution. In conventional housing, the most frequent indoor temperature is 20°C, representing 24.3%. Humidity performance further highlights the advantage of smart housing: the relative humidity distribution centers around 73.6% and is largely contained within the 50–70% comfort interval, whereas ordinary housing experiences humidity above 70% for as much as 27.8% of the time, increasing the likelihood of condensation.

Across the year, smart housing energy use displays clear peak and off-peak cycles. Higher consumption typically appears in December, January, February, June, July, and August, while lower-demand months include March, April, May, September, October, and November. For most energy categories and subcategories, usage rises during working hours and reaches its highest level between 9:00 AM and 5:00 PM. Total energy demand is greater on Floors 1 and 5, whereas Floors 3 and 7 exhibit comparatively lower overall consumption. Finally, as the proportion of influencing factors increases, the marginal energy-saving benefit declines, shifting from 3% at 4,629.52 yuan/m^2 to 13% at 2,023.47 yuan/m^2.

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