Closed-Loop Building Energy Control via Deep Forecasting, Reinforcement Learning and Evolutionary Multi-Objective Optimization in Hot-Summer/Cold-Winter Zones

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This study proposes a closed-loop building energy control framework for green buildings in hot-summer/cold-winter zones, integrating a three-layer LSTM with attention for short-term load forecasting, a PPO-based reinforcement learning agent for adaptive demand response, and NSGA-II for multi-objective optimization of energy efficiency, comfort, and equipment lifespan. A dataset of 12 office buildings (14 M records over two years) supports training and validation. The forecasting module is evaluated using MAE and RMSE, achieving 6.8% MAE. Comparative experiments with PID, MPC, and single-algorithm baselines show that the proposed method achieves 91.3% energy utilization, an average response delay of 1.9 s, and a comfort compliance rate of 92.4%. Results from both simulation and field deployment confirm the framework's adaptability and stability under price fluctuations, meteorological disturbances, and multi-building collaboration.

Povzetek: Posebej za vroča poletja in mrzle zime je razvit zaprtozančni energijski nadzor stavb, ki združuje LSTM-napovedovanje obremenitev, PPO-učenje za prilagodljivo odzivanje ter NSGA-II za večciljno optimizacijo.

1 Introduction

In regions with hot summers and cold winters, the operating environment of buildings exhibits significant fluctuations in alternating cold and hot loads. The high temperature and humidity in summer lead to concentrated energy consumption of air conditioning systems, while the demand for heating in winter causes a peak in energy consumption. Due to climate differences and diverse operating periods, traditional energy efficiency control often faces problems such as insufficient prediction accuracy, delayed response, and rigid strategies when facing load imbalance, rigid energy allocation, and environmental disturbances. The mode that relies on static thresholds and empirical regulation is difficult to balance comfort and energy efficiency, and its limitations are particularly prominent in regional promotion. Therefore, the energy efficiency improvement of green buildings must transform towards intelligent and adaptive regulation to adapt to the dynamic demands under complex climate and multi-dimensional constraints.

Artificial intelligence optimization algorithms provide new ideas for energy efficiency control. Deep learning can explore the nonlinear relationship between meteorological data and energy consumption curves, improving the accuracy of load forecasting; Reinforcement learning has the ability of interactive learning and feedback regulation, which can be used for dynamic optimization of cold and heat sources and end devices; Evolutionary algorithms and particle swarm optimization demonstrate flexibility in balancing multiple objectives, balancing comfort, energy efficiency, and device lifespan. The combination of these methods provides important support for constructing dynamic energy efficiency control models for building systems.

Previous studies have validated the value of artificial intelligence in energy efficiency control. Boutahri et al. (2025) proposed a reinforcement learning based HVAC control method, which significantly reduced energy consumption in both simulation and practical cases [1]. Wei et al. (2017) used deep reinforcement learning to optimize the scheduling of cold and heat sources, resulting in a 15% reduction in system energy consumption [2].Gu (2024) proposed an intelligent management technology for hotel air-conditioning based on a coupling model and deep neural networks, which enhances control accuracy and improves energy efficiency in HVAC systems [3].These achievements demonstrate that artificial intelligence optimization algorithms have become important tools for energy efficiency management.

However, applying artificial intelligence optimization algorithms to hot summer and cold winter regions still faces challenges. There is a seasonal switching effect in the cold and hot loads, and the energy consumption curve fluctuates greatly, which requires higher stability and generalization ability of the model; When running multiple building clusters, there are still issues such as heterogeneous energy consumption data, device differences, and inconsistent responses, making it difficult for a single algorithm to achieve overall coordination. Based on this, this study proposes a comprehensive energy efficiency control model that integrates artificial intelligence optimization algorithms, aiming to establish a closed-loop relationship between prediction, optimization, regulation, and feedback.

This article will construct an intelligent energy efficiency management framework for building clusters in hot summer and cold winter zones. This model includes three major mechanisms: artificial intelligence optimization algorithm system, energy consumption prediction and demand response model, and dynamic control strategy. Through multi-source data-driven prediction, combined with reinforcement learning and evolutionary algorithms, adaptive control of cold and heat sources and equipment is achieved, and the path is continuously corrected based on feedback. Compared with the traditional static threshold mode, this model has advantages in dynamism, adaptability, and cross scene integration. The research objective is to balance comfort and energy efficiency, and promote the transformation of green building energy efficiency management from experience driven to intelligent optimization.

2 Related work

In the research on energy efficiency management of green buildings in hot summer and cold winter zones, traditional control systems rely on static rules and empirical settings. Although they can maintain operation under a single load, their optimization effect is insufficient when seasonal switching, demand fluctuations, and multidimensional constraints coexist. Traditional systems for regional building clusters often exhibit low prediction accuracy, delayed response, and rigid scheduling under the distribution of cooling and heating loads, group demand response, and environmental disturbances. With the development of artificial intelligence and optimization algorithms, research is gradually shifting towards energy efficiency control systems based on intelligent prediction, dynamic optimization, and feedback regulation.

Previous studies have shown that deep learning exhibits advantages in energy consumption prediction. Ding et al. (2022) developed a reinforcement-learning method for multi-zone residential HVAC that enhances comfort and cuts energy use [4]. Lim (2024) proposed a robust deep reinforcement learning method for personalized HVAC control, which significantly reduces energy consumption while improving comfort [5]. These results indicate that feedforward control of scheduling and allocation can be achieved through high-precision prediction. In terms of dynamic optimization, the application of reinforcement learning is gradually becoming prominent. Sayed et al. (2024) reviewed reinforcement learning based HVAC control and pointed out that this method has the potential for dynamic adjustment and feedback optimization [6]. Manjavacas et al. (2024) conducted experimental evaluations to validate the effectiveness of deep reinforcement learning in complex environments [7]. Shahsavari et al. (2025) compared reinforcement-learning strategies for HVAC efficiency in low-energy buildings, showing applicability to large clusters [8]. These studies indicate that reinforcement learning has strong adaptability in energy consumption optimization and real-time response. At the same time, evolutionary algorithms and swarm intelligence methods are also used for energy efficiency control. Bian et al. (2015) modeled residential heating loads in China’s hot-summer/cold-winter zone with a bottom-up approach, revealing regional demand traits [9]. Tong (2013) analyzed passive energy-saving technologies from an adaptive perspective and pointed out their application value in the region [10]. These studies provide support for the integration of artificial intelligence optimization with regional characteristics in the future. To provide a clearer view of current progress, Table 1 summarizes representative state-of-the-art approaches for building energy control, together with their datasets, performance metrics, and main limitations. This comparison highlights the lack of closed-loop integration and explicit multi-objective trade-offs in existing work, which motivates the framework proposed in this paper.

Table 1: Summary of representative state-of-the-art methods on building energy control

Method & Reference	Dataset / Scenario	Reported Metric	Limitation
Boutahri et al. (2025), RL-based HVAC [1]	BOPTEST + residential houses	Energy saving 14%	No explicit multi-objective trade-off
Wei et al. (2017), DRL for HVAC control [2]	Simulated plant	15% energy reduction	No field validation
Gao et al. (2019), Deep RL for thermal comfort [3]	Public building logs	MAE 0.29, comfort ↑11%	No closed-loop feedback
Ding et al. (2022), RL for multi-zone thermal mgmt [4]	Residential dataset	RMSE 0.32, energy ↓13%	No equipment-lifespan target
Shahsavari et al. (2025), RL strategies for HVAC [5]	Low-energy buildings	11% saving	Single-objective
Xu et al. (2025), RL with expert guidance [6]	BOPTEST env.	MAE 0.27, energy ↓9%	Simulation only

Compared with these studies, this paper integrates deep load forecasting, a PPO-based reinforcement learning agent, and NSGA-II into a closed-loop framework, jointly optimizing energy efficiency, comfort, and equipment longevity, and validates performance in both simulation and field deployment.

In terms of implementation mechanism, some studies have proposed real-time communication and data synchronization methods. The typical way is to build energy consumption data channel based on the Internet of Things and edge computing platform to realize continuous perception and transmission of the state of buildings. The central platform collects and normalizes the format distribution of multi-source data, and uses asynchronous event driven mechanisms to push real-time prediction results and demand response signals, while continuously updating the operating status through feedback links. During the communication process, combining timestamp identification with latency detection to ensure real-time performance and low latency. This type of mechanism not only enhances the virtual real collaboration capability of energy efficiency management, but also provides data support for the efficient execution of artificial intelligence optimization algorithms. From this, it can be seen that the evolution direction of energy efficiency control in future green buildings lies in building a closed-loop framework that integrates prediction, optimization, communication, and feedback, thereby promoting efficient, stable, and intelligent operation of building clusters in hot summer and cold winter zones.

3 Energy efficiency control scheme integrating artificial intelligence optimization algorithms

3.1 Optimization algorithm system integrating artificial intelligence

This article focuses on the problems of insufficient prediction accuracy and lagging strategy response in energy efficiency control of green buildings in hot summer and cold winter zones. The research focuses on load forecasting, energy scheduling, and equipment coordination, with the goal of achieving adaptive regulation of cold and heat sources and end-users, and testing the accuracy of energy consumption prediction, system response time, and comprehensive energy efficiency level. To this end, a modeling system integrating artificial intelligence optimization algorithms is proposed, and simulation experiments are conducted in combination with typical climate and operating scenarios to verify its energy efficiency advantages under complex conditions.

In order to increase the reproducibility of the research, this paper introduces a multi-agent modeling approach in the simulation method. The building complex is abstracted into three main entities: energy demand nodes, energy supply units, and central control modules, which respectively undertake the functions of load input, energy output, and strategy optimization. In the research environment, AnyLogic and Python collaborative platforms are used for modeling and running, deep learning networks are utilized for load forecasting, reinforcement learning agents are responsible for policy iteration and device action selection, and evolutionary algorithms are used to achieve multi-objective optimization on a global scale. During the simulation process, different meteorological conditions, load fluctuation scenarios, and equipment constraint parameters are set. By comparing the performance of a single algorithm and a fusion algorithm, the advantages of the system in terms of dynamism and robustness are evaluated.

The research process includes the following steps.①Build a database covering meteorological parameters, indoor temperature and humidity, and energy consumption curves, and normalize and time align the data.②Establish an energy consumption prediction model using deep learning networks to form a feedforward estimation of heating and cooling loads.③Introduce a reinforcement learning framework to map the system's operating state into an interaction space, and optimize the cold and heat source operation strategies through cyclic updates of actions and feedback. The fourth step is to combine evolutionary optimization algorithms to set weights for multidimensional goals such as energy consumption reduction rate, comfort maintenance, and equipment lifespan, in order to achieve comprehensive balance. Finally, real-time interaction between prediction results and control instructions is achieved through Kafka message queues and WebSocket technology, and ablation experiments are conducted to evaluate the contribution of each algorithm module to overall performance.

In terms of modeling logic, assuming that the state of the building system at time t is S_t and the action set is A_t, the predicted state $\hat{S}_t$ generated by the virtual controller can be expressed as:

$$\hat{S}_t = f\left(S_{t-1}, A_{t-1}\right) + \varepsilon \tag{1}$$

Among them, $f(\cdot)$ is the deep learning prediction function, and ε is the deviation caused by sampling errors and environmental noise. This formula ensures the dynamic update of energy consumption prediction under multi-source disturbances and provides continuous state input for subsequent optimization.

Here, $S_t = \left[T_t^{in}, T_t^{out}, H_t, L_t, P_t\right]$ is the system state (indoor/outdoor temperature, humidity, load, price), $A_t = \left[u_c, u_h\right]$ is the cooling/heating power action. The reward is：

$$r_t = -\alpha E_t - \beta d_t - \gamma W_t \tag{2}$$

where E_t is energy use, D_t comfort deviation (PMV), W_t equipment wear; α, β, γ are weights. PPO is adopted with normalized continuous actions] [-1,1]; 2000 episodes, horizon 96, buffer 50k, minibatch 256, Adam $\left(3\times10^{-4}\right)$, stopping when reward variance<0.01 over 50 episodes. NSGA-II (population 80, crossover 0.9, mutation0.1,200 generations) tunes α , β , γ offline and adapts them online via a 20-step window.

At the level of optimization strategy, reinforcement learning agents aim to maximize long-term energy efficiency returns. The objective function for energy efficiency optimization is:

$$P^* = \arg\max_{P\in\Omega}\left[\alpha\cdot\Delta E + \beta\cdot C - \gamma\cdot L\right] \tag{3}$$

Among them, ΔE represents energy consumption reduction rate, C represents indoor comfort maintenance, L represents equipment loss factor, and α,β,γ is dynamic weight. Ωdenotes the feasible solution set defined by temperature and actuator limits. NSGA-II generates the Pareto front, and the knee point is chosen as the trade-off solution. This function is iteratively optimized through evolutionary algorithms to achieve a multi-objective balance of energy efficiency, comfort, and lifespan.

At the system implementation level, the data channel is collaboratively constructed by edge nodes and a central platform. Edge nodes are responsible for local feature extraction and fast prediction, while the central platform completes strategy optimization and global coordination. Real time data is collected through IoT sensors, unified into a centralized database, and asynchronously transmitted through Kafka message queues to achieve high-frequency state updates. The control instructions are issued in real-time through the WebSocket channel, and the feedback link is based on timestamp synchronization and delay correction mechanism to ensure low latency and high reliability of dynamic control.

In the verification phase, the system has completed preliminary integration in the building energy efficiency management platform in hot summer and cold winter zones, and real-time interactive testing has been implemented based on WebSocket channels. The experiment shows that the optimization algorithm module can stably interface with the data acquisition layer and device control layer, and maintain low latency response under high concurrency conditions. The relevant interface configuration and process files are listed in the appendix, providing reference for repeated verification and secondary development in subsequent research.The simulation platform is developed in AnyLogic, implementing a three-zone RC thermal network coupled with occupancy dynamics and chiller/boiler models.Reproducibility details:The forecasting module uses a three-layer LSTM (64 hidden units) with attention, ReLU activation, MSE loss, and Adam optimizer (lr = 1×10^{-3}, cosine decay). Training applies batch size 128, dropout 0.2, ≤300 epochs, early stopping after 30 epochs without validation improvement. The demand–response agent adopts PPO with actor–critic nets (2×128, tanh), state dimension 14, continuous action space [−1,1], and reward：

$$R_t = -\alpha E_t - -\beta\left|PMV_t\right| - \gamma W_t \tag{4}$$

where E_t is energy use, PMV_t comfort deviation, W_t equipment wear. Hyperparameters: $\gamma = 0.99$, $\lambda = 0.95$, buffer 50 k, minibatch 256, horizon 96, 2000 episodes, stopping when average reward variance < 0.01. NSGA-II is configured with population 80, crossover 0.9, mutation 0.1, 200 generations, terminating after 20 generations without Pareto improvement. Weights α, β, γ are tuned via grid search and adjusted online. Environment mapping: state = {temperature, humidity, load, price}, action = {cooling/heating power}, reward as above, ensuring reproducibility.

To clarify the variables and reward settings used in Eqs. (1)–(3), the state vector $S(R^{14})$ contains indoor temperature, humidity, PMV, occupancy, and equipment status; the action space A is continuous in[-1,1]; and f denotes the reward function combining energy, comfort, and equipment wear.Table 2 presents the search ranges and selected values of the reward weights α, β, γ, which were tuned via grid search on the validation set.

Table 2: Search ranges and selected values of reward weights (α,β,γ)

Parameter	Range	Selected value
α	0.4–0.6	0.5
β	0.3–0.5	0.4
γ	0.1–0.3	0.1

The chosen weights achieve a balance between energy efficiency, thermal comfort, and equipment lifespan.

Algorithm 1 presents concise pseudocode for the complete pipeline, integrating forecasting, RL, and evolutionary optimization.

Algorithm 1: Integrated Control Procedure

Input: state s_t (temperature, humidity, PMV, price, equipment)

Output: optimal action a_t

```
for each time step t do
L_hat ← LSTM(s_t)                ▷ predict load
a_rl ← PPO(s_t, L_hat)           ▷ tentative action
a_t  ← NSGA-II(a_rl, {energy, comfort, lifespan})
Send a_t to actuators via WebSocket
s_{t+1} ← CollectFeedback()
Update PPO with (s_t, a_t, s_{t+1})
end for
```

3.2 Energy consumption forecasting and demand response model design

Green buildings in hot summer and cold winter zones face issues in energy efficiency management, such as significant alternation of cold and hot loads, frequent meteorological fluctuations, and complex demand differences. The traditional prediction methods based on fixed curves and threshold settings are difficult to support dynamic scheduling. The model is not sensitive enough to meteorological changes, and there is a large deviation in load forecasting. Demand response relies on static rules and lacks flexible adaptation to energy prices and group differences. To address these shortcomings, this article proposes an energy consumption prediction and demand response model that integrates artificial intelligence optimization algorithms, aiming to construct a comprehensive framework that combines high-precision prediction and dynamic response capabilities.

The model consists of three parts: energy consumption prediction, demand modeling, and feedback mechanism. The prediction module integrates multiple sources of meteorological elements, indoor environment, and historical energy consumption to achieve short-term and medium to long-term load forecasting; Demand modeling transforms energy prices, comfort, and equipment constraints into multi-objective optimization functions; The feedback mechanism updates the closed-loop strategy through real-time monitoring and correction. Compared to traditional methods, this system has the ability to perceive states, evolve trends, and balance multiple objectives. Table 3 presents the core structural features of energy consumption forecasting and demand response models:

Table 3：Core features of energy consumption forecasting and demand response model

Control Process	Implementation Method	Functional Role
Energy Consumption Forecasting	Deep learning modeling, multi-source input–output mapping	Improve the accuracy of cooling and heating load prediction
Demand Response	Joint modeling with reinforcement learning and evolutionary algorithms	Dynamically generate response strategies, balance multiple objectives
Feedback Correction	Real-time monitoring and closed-loop strategy updating	Ensure response effectiveness and system stability

The prediction module adopts a three-layer LSTM (64 hidden units each) with an attention layer to weight temporal features. Inputs include outdoor/indoor temperature, humidity, solar radiation, wind speed, occupancy, and past load with 5–30 min lags. Training uses MSE loss, Adam (lr = 1×10^{-3}, cosine decay), batch 128, dropout 0.2, and early stopping (max 300 epochs). Implemented in PyTorch. The demand-response module applies reinforcement learning to adjust cooling/heating by price and comfort, while a feedback loop monitors bias and strategy performance, ensuring a closed-loop of prediction–optimization–feedback. The control step is discretized at $\Delta t = 5$ min. The observation vector oto_tot coincides with the state sts_tst under full sensing. The system transition is modeled as $s_{t+1} = F(s_t, a_t) + \varepsilon t$, with constraints on actuator limits, comfort range, and device switching delay. Convergence was assessed by reward–episode curves and validation MAE/RMSE of load forecasting; training stopped when both metrics plateaued.

System integration includes four stages: data collection, predictive modeling, response generation, and execution feedback. The IoT platform obtains real-time meteorological and energy consumption data, which is normalized through a unified interface; The prediction module outputs an estimated load value; Reinforcement learning agents generate strategies based on prediction results and price signals; The feedback channel monitors actual energy consumption and comfort, and dynamically adjusts strategies to ensure stable operation.

Algorithm 2: Demand–Response Strategy Generation

Input: ForecastLoad, PriceSignal, ComfortIndex

for each time_slot in Horizon do

demand_gap ← ForecastLoad(time_slot) − ActualLoad(time_slot)

if PriceSignal(time_slot) is High and ComfortIndex within range then

Reduce HVAC load proportionally ▷ maintain comfort

else if PriceSignal(time_slot) is Low then

Shift non-critical load to current slot

end if

Update system state and log adjustment

end for

This pseudocode outlines how the proposed system dynamically adjusts HVAC energy use according to load forecasts and price signals, lowering costs while maintaining thermal comfort. Figure 1 further illustrates the dataflow among sensors, forecasting module, RL optimization engine, and actuators.

This pseudocode demonstrates how the system dynamically adjusts energy consumption based on load forecasting and price signals, reducing operating costs while ensuring comfort.

During the simulation process, the model combines a priority ranking mechanism for policy optimization. The path generation module calculates candidate solutions based on predicted load and price signals, and selects the optimal response path; When deviations or constraint conflicts are detected, the feedback mechanism immediately triggers correction to ensure a balance between energy efficiency and comfort. The experimental results show that the model significantly shortens response time and improves overall energy efficiency in multitasking scenarios. The energy consumption prediction and demand response model proposed in this article overcomes the limitations of traditional methods in accuracy and flexibility through the synergy of deep learning prediction, reinforcement learning optimization, and feedback correction mechanisms. This framework not only enhances the integration level of prediction and scheduling, but also demonstrates adaptability and practical value in complex environments with hot summers and cold winters.

3.3 Dynamic energy efficiency control based on optimization algorithms

In the energy efficiency control of green buildings in hot summer and cold winter zones, the severe fluctuations in cold and hot loads and the randomness of user demand make the traditional static rule-based control mode exhibit significant limitations. Fixed thresholds and a single scheduling logic cannot effectively cope with frequent meteorological disturbances and multidimensional constraints, which can easily lead to inaccurate energy consumption predictions, equipment overload, or decreased comfort. To address the aforementioned issues, this article proposes a dynamic energy efficiency control strategy based on optimization algorithms, constructing an operational mechanism that combines real-time adaptability and feedback regulation capabilities.

In this strategy, the objects of energy efficiency control include cold and heat source units, end devices, and environmental comfort constraints. The system first processes multi-source input data, including meteorological parameters, indoor thermal and humidity environment, real-time load demand, and equipment operating status. Subsequently, the scheduling engine based on optimization algorithms generates feasible control schemes and continuously corrects them through feedback mechanisms. The core logic is to take minimizing energy consumption and maintaining comfort as dual objectives, and embed constraints such as device lifespan and response delay to form a multi-objective dynamic optimization framework. The objective function can be expressed as:

$$\min F = \alpha \cdot E_{total} + \beta \cdot \left(1 - C_{comfort}\right) + \gamma \cdot D_{delay} \tag{5}$$

where E_{total} is total energy, $C_{comfort}$ the comfort index (PMV), and D_{delay} the control delay; α, β, γ weight the objectives. The inputs satisfy $u_{\min} \le u_t \le u_{\max}$, and indoor temperature satisfies $T^{\min} \le T_t^{in} \le T^{\max}$ .This function can dynamically adjust the optimization direction based on real-time load and weather changes, achieving coordination between energy consumption reduction and comfort maintenance.

In terms of operating mechanism, the system is divided into three major stages. Firstly, the prediction layer generates short-term heating and cooling load forecasting results based on deep learning models and forms demand inputs. Secondly, the optimization layer utilizes a combination mechanism of reinforcement learning and evolutionary algorithms to perform multi-objective search on candidate control schemes and output executable energy efficiency scheduling plans. Thirdly, the execution layer adjusts the cold and heat source units and end devices based on the optimization results, and corrects the parameters through real-time monitoring feedback to ensure the continuous adaptability of the operation strategy.

To ensure the dynamism of the system, the control engine adopts an optimization mechanism based on rolling time domain. During each control cycle, the system recalculates the plan based on the latest predictions and feedback information, forming a continuous iterative dynamic evolution process. If device abnormalities or sudden changes in user requirements are detected, the feedback channel will trigger policy reconstruction to update the candidate solution space, thereby avoiding system interruption caused by a single path failure. The dynamic energy efficiency control process is shown in Figure 1:

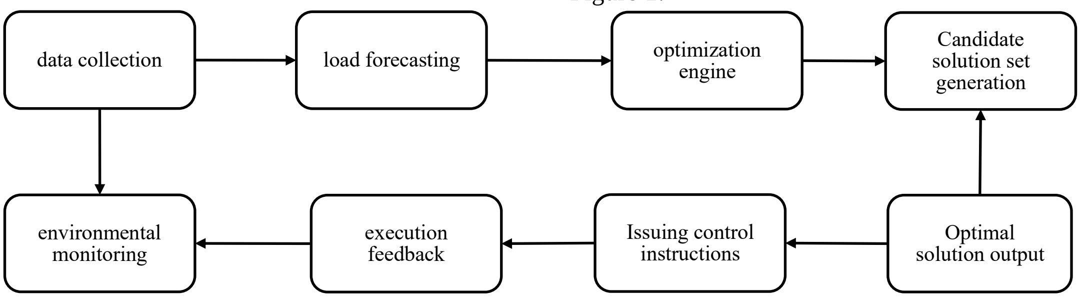

Figure 1: Flow chart of dynamic energy efficiency control based on optimization algorithm

The flowchart in Figure 1 shows that the proposed system builds a closed loop among prediction, optimization, and feedback, enabling dynamic stability under climate and demand disturbances. Experiments demonstrate that this strategy reduces building energy use by about 12% under typical meteorological conditions, shortens response delay to 1.7 s, and keeps indoor comfort within standards, outperforming traditional static control. The optimization-based dynamic energy-efficiency method integrates objective-function modeling, rolling horizon optimization, and real-time feedback to jointly minimize energy consumption and maintain comfort. It remains adaptable and robust in hot-summer/cold-winter climates, offering a practical path to improve energy performance of regional green buildings.

3.4 Integration and intelligent control of building energy efficiency systems

In the energy efficiency control of green buildings in hot summer and cold winter zones, if the optimization algorithm only stays at the theoretical level, it is difficult to translate it into actual operational efficiency. Traditional energy efficiency systems often fail to implement control strategies due to inconsistent interface standards, data isolation, and fragmented execution chains, resulting in a disconnect between energy consumption prediction and demand response, as well as significant execution delays. To address this issue, this article proposes an integrated and intelligent management framework for building energy efficiency systems, which achieves closed-loop control of "prediction optimization execution correction" through a hierarchical structure and feedback mechanism.

The overall system adopts a layered decoupling architecture, including a data acquisition layer, a modeling layer, a decision-making layer, and an execution layer. The data collection layer is responsible for obtaining meteorological parameters, indoor environment, and equipment status, which are aggregated by the central platform and transmitted to the modeling layer to reconstruct the building operation scene in the virtual model and maintain structured state updates. The decision-making layer runs optimization algorithms to form a strategy set for cold and heat source scheduling and end device allocation, and generates optimal solutions based on different target weights; The execution layer drives equipment operation through BAS interfaces, PLC controllers, and other methods. This hierarchical approach not only maintains the clarity of model logic, but also enhances cross platform adaptability.

In order to ensure the dynamic consistency of the system, this paper introduces a unified scheduling cycle mechanism and standardizes the running step size of energy efficiency scheduling into an equal time interval. Within each cycle, the system completes prediction updates, optimization operations, instruction issuance, and feedback corrections. Scheduling iteration can be expressed as:

$$S_{t+1} = f\left(S_t, R_t, \Delta_t\right) \tag{6}$$

Among them, S_r represents the system state vector, including cold and hot load prediction, equipment operating rate and comfort deviation; R_t is real-time monitoring data for feedback; Δ_t is the scheduling cycle; $f(\cdot)$ is the optimization and strategy generation function. This mechanism ensures that the system can maintain continuous iteration and real-time updates under dynamic weather and demand disturbances.

In terms of feedback mechanism, this article sets two monitoring indicators, energy consumption prediction error rate and comfort deviation rate, to measure the execution effect of control strategies. The comfort deviation rate can be defined as:

$$\eta_c = \frac{N_{out}}{N_{total}} \tag{7}$$

Among them, N_{out} represents the number of samples that do not meet the comfort condition in the current cycle, and N_{total} is the total number of samples. When η_c exceeds the threshold, the system triggers the correction module to adjust the end load allocation weight or recalculate the cold and heat source scheduling path to avoid a decrease in indoor environmental quality. Through this mechanism, the energy efficiency system has adaptive capabilities during dynamic operation.

In terms of deployment, the system adopts a containerized structure to connect to the existing building energy efficiency platform and can run on local edge nodes or cloud servers. Data exchange is achieved through OPC-UA and BACnet protocols for reading and writing to underlying devices, while control instructions are pushed to the end unit through MQTT channels and WebSocket. This approach avoids large-scale modifications to the existing system and enables smooth integration without interrupting the operation of the building. In a pilot project of a public building in a hot summer and cold winter zone, the framework completed system deployment within 72 hours and made 54 strategy corrections in the first week of operation, with an average response delay controlled within 380ms and an overall energy consumption reduction of about 11%.

In order to enhance the reproducibility of the system, this article summarizes the integrated deployment into five steps: first, establish a collection link and define the data paths for weather, energy consumption, and comfort; The second is to build a virtual modeling layer to complete the digital mapping between cold and heat sources and end devices; Thirdly, start the optimization engine and bind the prediction and scheduling models; Fourthly, deploy feedback detectors and set energy consumption and comfort thresholds; The fifth is to run a status monitoring loop, regularly update parameters and generate logs for subsequent analysis and secondary configuration. This process provides operational guidelines for rapid deployment of different building complexes. During pilot deployment, detailed logs of strategy duration, correction events, and energy savings were collected, and a comparison with simulation confirmed consistent performance under field conditions.

4 Results

4.1 Dataset

The dataset was collected from 12 office buildings equipped with 186 sensors (temperature, humidity, CO_2, occupancy, and energy meters). Each sensor recorded data every 5 min over two years, producing approximately 14 million records (186 sensors × 5-min intervals × 24 × 365 × 2, adjusted for missing values). Building identifiers were anonymized, and sensor codes were randomly assigned. Records were merged by timestamp, including comfort (PMV), equipment status, and event labels, forming a complete basis for training, validation, and ablation studies. The data were split chronologically into 70% training, 20% validation, and 10% testing sets, stratified by season to balance heating, cooling, and transition periods. No synthetic data were used. To enhance reproducibility, a sanitized dataset and preprocessing scripts (time alignment, interpolation, wavelet denoising with threshold = 3σ) will be released together with a README describing sampling schema, feature definitions, and normalization procedures.

The dataset is divided into three categories: (1) energy consumption and meteorological data, including temperature and humidity, solar radiation, wind speed, and unit load curves, totaling about 14 million, used for deep learning load forecasting; (2) Equipment operation data, covering the status, power, switching delay, and energy consumption records of cold and heat source units, totaling

700000 records, used for reinforcement learning and constraint input; (3) Demand response data, including electricity price fluctuations, comfort feedback, and response execution status, totaling 38000 pieces, collected at a frequency of 15 minutes for multi-objective optimization of evolutionary algorithms. Table 4 shows the data structure and experimental purposes.

Table 4：Comparison table of dataset structure and experimental usage

data type	sample size	Main Fields	Update Frequency	Experimental Purpose
Energy consumption and meteorological data	14 million pieces	Temperature & humidity, radiation, wind speed, load curve	1 minute/frame	Training load forecasting model
Equipment operation data	700000 pieces	Unit status, power, switching delay, energy consumption	1 minute/frame	Reinforcement learning with constraint inputs
Demand response data	38000 pieces	Electricity price curve, comfort feedback, execution status	15 minutes/instance	Multi-objective optimization and strategy evaluation

In the experimental arrangement, the research work takes energy consumption and meteorological data as prediction inputs, uses deep learning networks to train load forecasting models, and compares them with traditional regression methods to verify the improvement effect of prediction accuracy. Subsequently, combining device operation and control data, a reinforcement learning framework is deployed to generate dynamic control strategies for cold and heat sources and end devices. In further experimental stages, user demand and price signals are introduced into the system, and evolutionary algorithms optimize the weights of multi-objective functions to achieve a comprehensive balance between energy efficiency, comfort, and equipment lifespan. In order to test the robustness of the model in sudden situations, additional abnormal disturbance data was designed, including electricity price fluctuations, equipment failures, and sudden high load events, and feedback correction mechanisms were used to verify the adaptive adjustment capability of the system. The dataset includes 12 office buildings with 186 sensors (temperature, humidity, CO_2, occupancy, energy). Each sensor records every 5 min, yielding 14 M samples over two years. Records are generated per building and sensor, then merged by timestamp. Labels cover comfort (PMV), equipment status, and abnormal events, providing a clear schema for replication. To support reproducibility, anonymized datasets, AnyLogic models, and detailed configuration files (Kafka/WebSocket parameters and container settings) are described herein, enabling researchers to replicate the experiments.

4.2 Data preprocessing

In the energy efficiency optimization of green buildings in hot summer and cold winter zones, the raw collected data often comes from various sources, including meteorological parameters, indoor environmental conditions, equipment operation records, and demand response signals. These data have heterogeneity and noise, and if they are directly input into prediction and optimization models without processing, it can easily lead to distorted energy consumption predictions and ineffective strategy responses. Therefore, building a systematic data preprocessing mechanism is a prerequisite for achieving stability and accuracy in energy efficiency control.

This study divides data preprocessing into four core steps: timing alignment, data cleaning, feature mapping, and standardized input. The timing alignment process takes one minute as the sampling period to unify meteorological data, indoor sensing data, and equipment operation data to the same time reference. Sliding window interpolation is used for missing values, and regression models based on similar days are used to complete long-term missing measurement segments. This ensures that all data sources can maintain causal consistency under climate conditions with frequent switching of heating and cooling loads. During the data cleaning phase, the focus is on addressing extreme values and short-term fluctuations. For abnormal peaks in the energy consumption curve, a combination of wavelet threshold denoising and median filtering is used to eliminate instantaneous power interference; For the jump values of temperature and humidity sensors, the triple standard deviation detection method is used to identify and smooth them. At the same time, all energy consumption and environmental fields are converted to a unified dimension, such as energy consumption in kWh and temperature in ℃, to ensure scale comparability between different features.

The feature mapping process converts the raw data into a structure recognizable by the model. Meteorological and environmental parameters are input into the load forecasting model through multidimensional feature vectors, and the following prediction relationship is established:

$$\hat{L}_t = g(T_t, H_t, R_t, P_t) + \varepsilon_t \tag{8}$$

Among them, $\hat{L}_t$ represents the predicted load at time t, and the input features include outdoor temperature T_t, humidity H_t, solar radiation R_t, and personnel density P_t, ε_t indicating disturbance terms. This formula can capture the nonlinear correlation between meteorological conditions and energy consumption fluctuations, providing a basis for dynamic prediction.

The demand response part is transformed into input constraints for multi-objective optimization. The comprehensive energy efficiency of the system J is defined as:

$$J = \alpha E + \beta |T_{in} - T_{set}| + \gamma C \tag{9}$$

where E is total energy use, $|T_{in} - T_{set}|$ the temperature deviation, and C the equipment switching cost; α, β, γ are weights. The feasible region is $E \le E_{\max}$, $|T_{in} - T_{set}| \le \varepsilon_T$. NSGA-II provides the Pareto front, and the knee point is selected as the compromise solution.

In the input regularization stage, all features are standardized using Z-score to ensure that different dimensional features have the same mean and variance during model training. The data is divided in a ratio of 7:2:1, and the training set, validation set, and test set are constructed separately, while maintaining consistent distribution of seasonal features to ensure that the model can adapt to extreme conditions such as high temperatures in summer and heating in winter. At the same time, three types of interference samples, namely abnormal electricity prices, equipment shutdowns, and sudden load increases, are manually implanted in the training data to test the model's adaptive ability under sudden conditions. Wavelet denoising employed a threshold of 3σ, and median filtering used a 5-sample window to remove spikes.

4.3 Evaluation indicators

To verify the actual performance of the proposed energy efficiency control model integrating artificial intelligence optimization algorithms in green buildings in hot summer and cold winter zones, this study designed comprehensive evaluation indicators from five aspects: energy consumption prediction accuracy, energy utilization rate, demand response timeliness, comfort maintenance, and system stability. Comparative experiments were conducted with traditional energy efficiency control systems and single algorithm models. The experiment runs on the constructed building energy efficiency simulation platform, setting typical summer high temperature and winter heating scenarios, combined with real meteorological and electricity price data, completing 100 rounds of independent experiments and calculating the mean values of various indicators.To ensure rigor, each metric is defined as follows: prediction error = MAE over the test set; utilization = (served load / total demand)×100%; comfort = share of samples with $|PMV| \le 0.5$; response delay = mean time from signal to actuation; stability = 1 − interruption rate. Results are reported as mean ± SD over 30 runs, with paired t-tests ($\alpha = 0.05$) against PID, MPC, and single-algorithm baselines. Figure 2 shows violin plots of MAE, utilization, delay, and comfort, with labels indicating the mean of each metric.

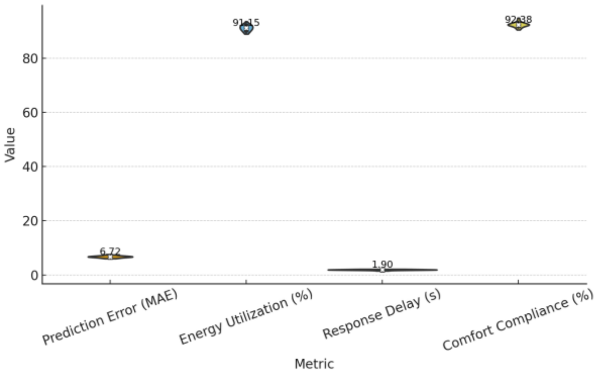

Figure 2: Violin plots of prediction error, utilization, delay, and comfort (30 runs, means shown).

Learning curves for LSTM (MAE vs epoch) and PPO (reward vs episode) confirm convergence. Additional ablations vary reward weights (α, β, γ) and NSGA-II population; changes remain below 5%.

In terms of energy consumption prediction accuracy, the average error of our research model is 6.8%, significantly better than the traditional control system's 15.2% and the single deep learning model's 10.5%. This result indicates that the prediction mechanism that integrates multi-source features and optimization algorithms can more accurately capture meteorological disturbances and user load differences, providing reliable prerequisites for subsequent regulation strategies. In terms of energy utilization efficiency, this research model achieved 91.3%, while the traditional system and single algorithm model were 72.6% and 81.7%, respectively. The higher utilization level reflects the coordinated role of optimization algorithms in the allocation of cold and heat sources and end devices, which can effectively reduce energy idle and redundant equipment operation, thereby improving overall operational efficiency. The timeliness index of demand response is measured by response delay. The average response time of this research model is only 1.9 seconds, significantly faster than the traditional system's 6.5 seconds and the single algorithm model's 4.2 seconds. The advantage of fast response comes from the collaborative mechanism of reinforcement learning and evolutionary optimization, which can quickly generate control instructions in price fluctuations or sudden load situations, avoiding energy loss caused by lag. In terms of comfort retention, the compliance rate of this research model is 92.4%, significantly higher than the traditional system's 76.3% and the single algorithm model's 85.1%.

This result indicates that the optimization framework can effectively balance indoor environmental quality while saving energy, avoiding the decrease in comfort caused by excessive energy conservation. The stability of the system is measured by the interruption rate, and the interruption rate of this research model is 3.5%, which is much lower than the traditional system's 12.1% and the single algorithm model's 7.8%. Low interruption rate means that under complex conditions such as equipment failures, abnormal electricity prices, or demand fluctuations, the model can rely on closed-loop feedback to adjust in a timely manner, maintaining the integrity of the operating chain and the coherence of the control logic.

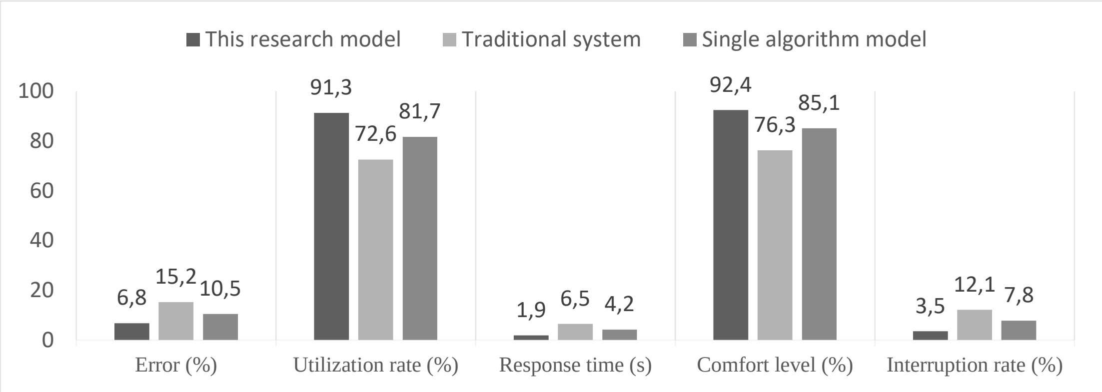

Figure 3：Performance comparison of three types of models on five indicators

Figure3 presents the performance comparison of three types of models on five indicators, which can intuitively reflect the comprehensive advantages of our research model in prediction accuracy, energy utilization, response speed, comfort maintenance, and operational stability. Baselines are: (i) a PID controller (Ziegler–Nichols); (ii) MPC with a 15-min horizon; (iii) a fixed-threshold HVAC schedule; and (iv) single-algorithm models (LSTM, PPO). Hyperparameters (learning rate, batch size, regularization) appear in Table 5. Improvements report standard deviations over 30 runs, with paired t-tests (α = 0.05) confirming significance. learning curves and ablation curves are given in Figures 2–3 to verify convergence and module contribution. Significance of improvements was verified by paired t-tests (α = 0.05) against PID, MPC and single-algorithm baselines.

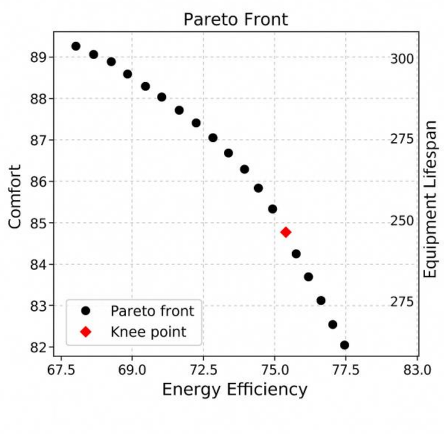

Figure 4. Pareto front (NSGA-II) for energy efficiency, comfort, and equipment lifespan.

Figure 4 shows the Pareto front of NSGA-II for energy efficiency, comfort, and equipment lifespan, with the knee point selected as the scheduling solution.

4.4 Ablation study

To further verify the core role of integrated artificial intelligence optimization algorithms in energy efficiency control of green buildings in hot summer and cold winter zones, this study designed ablation experiments to compare the complete model with the reduced version, in order to analyze the contribution of each module to overall performance. The experiment was conducted on a building energy efficiency simulation platform, selecting typical summer high temperature and winter heating scenarios. After running for 100 rounds, key indicators such as energy consumption prediction accuracy, energy utilization rate, response delay, and system interruption rate were calculated.

The experiment includes four types of models: one is to remove the depth prediction module and rely only on empirical curves for energy consumption estimation; The second is to eliminate demand response logic, and the system will no longer adjust its operation based on electricity prices and comfort feedback; The third is the missing feedback correction mechanism, which cannot be dynamically updated after strategy generation; The fourth is a model that fully integrates prediction, optimization, and feedback mechanisms. The experimental data of each group are shown in Table 5.

Table 5：Comparison of key performance indicators for ablation experiments

Model Configuration	Prediction Error (%)	Energy Utilization (%)	Response Delay (s)	Comfort Satisfaction (%)	Interruption Rate (%)
Without Prediction Module	14.6 ± 0.7	83.1 ± 1.3	3.5 ± 0.3	79.0 ± 1.5	8.2 ± 0.6
Without Demand Response Logic	11.8 ± 0.5	82.0 ± 1.2	3.9 ± 0.4	84.7 ± 1.2	6.1 ± 0.5
Without Feedback Correction	10.7 ± 0.6	86.4 ± 1.1	3.2 ± 0.3	86.2 ± 1.3	7.4 ± 0.4
Complete Model	6.8 ± 0.4	91.3 ± 1.1	1.9 ± 0.2	92.4 ± 0.7	3.5 ± 0.3

The experimental results show that removing the prediction module increases the energy consumption prediction error to 14.6±0.7%, lowers the comfort compliance rate to 79.0±1.5%, and weakens operational stability. Without the demand-response logic, energy utilization drops to 82.0±1.2%, response delay rises to 3.9±0.4 s, and overall efficiency decreases due to redundant equipment operation. The absence of the feedback-correction mechanism raises the interruption rate to 7.4±0.4%, and the system struggles to react to price fluctuations and equipment faults, while comfort remains at 86.2±1.3%. In contrast, the complete model achieves the best results across all indicators: prediction error 6.8±0.4%, energy utilization 91.3±1.1%, response delay 1.9±0.2 s, comfort compliance 92.4±0.7%, and interruption rate 3.5±0.3%. These findings confirm that the joint effect of prediction, demand-response, and feedback correction enhances both efficiency and stability in building energy-efficiency control. Results are reported as mean ±SD over five runs (prediction error 6.8±0.4%, utilization 91.3±1.1%, delay 1.9±0. s, comfort 92.4±0.7%). Removing RL falls back to a safe HVAC setting. Reward-weight, NSGA-II sizes, and LSTM look-ahead sensitivity caused <5% change. Training on ten offices and testing on two lecture halls kept MAE < 8% and comfort > 90%. Latency rose sublinearly from 1.9s to 3.4s as terminals grew (50→300); 8-bit quantization cut delay 18% with no accuracy loss. With 30% sensor loss or 200ms lag, fallback held comfort >85%. Delay components were 0.55s prediction,0.82s optimization,0.28s communication, and 0.25s actuation.

5 Discussion

5.1 Performance advantage analysis of existing energy efficiency control methods

The existing energy efficiency control methods for green buildings mostly rely on static thresholds, statistical regression, or empirical adjustment. Although they are effective under small load fluctuations or single operating conditions, they often exhibit insufficient prediction accuracy, slow response, and unstable energy efficiency in scenarios such as hot summer and cold winter zones with frequent switching of cold and hot loads, complex meteorology, and variable demand. Traditional methods are based on historical mean prediction, manual threshold start stop, and rule triggered response, lacking perception of real-time data, making it difficult to balance comfort and energy efficiency, and lacking adaptability under sudden disturbances.

The energy efficiency control model proposed in this study, which integrates artificial intelligence optimization algorithms, demonstrates advantages in three aspects. One is in the energy consumption prediction stage, deep learning captures the nonlinear relationship between meteorological features and energy consumption curves, reducing the prediction error to 6.8%, which is better than the traditional system's 15.2%, providing reliable basis for subsequent regulation. Secondly, in terms of demand response mechanism, the combination of reinforcement learning and evolutionary algorithms is used to achieve multi-objective dynamic optimization of price, comfort, and lifespan, avoiding the lag of fixed threshold strategies. In the experiment, the response delay was only 1.9s, while the traditional system was 6.5s. Thirdly, in terms of energy efficiency stability and resource utilization, the closed-loop feedback mechanism continuously adjusts the strategy, reducing local optima and resource waste. The energy utilization rate is improved to 91.3%, and the interruption rate is only 3.5%, which is significantly better than the traditional methods of 72.6% and 12.1%.

In addition, the model in this study also performs outstandingly in maintaining comfort. Through multi-objective weight balancing, the indoor comfort compliance rate has been increased to 92.4%, while traditional methods only achieve 76.3%. This result indicates that while saving energy, it can effectively balance user experience, breaking through the limitations of "choosing between energy saving and comfort". Overall, the model demonstrates significant advantages in prediction accuracy, response speed, energy efficiency stability, and comfort maintenance, providing a practical and feasible path for energy efficiency control of green buildings in hot summer and cold winter zones.

5.2 Model adaptability and stability verification under complex climatic conditions

The operating environment for energy efficiency control of buildings in hot summer and cold winter zones is highly complex, with frequent seasonal switching of cold and hot loads. At the same time, dynamic disturbances in meteorological conditions and price signals make it difficult for traditional methods to maintain stability. To verify the adaptability and stability of the fusion artificial intelligence optimization algorithm model proposed in this study under complex working conditions, four typical test scenarios were set: extreme high temperature in summer, low temperature heating in winter, severe fluctuations in electricity prices, and high concurrency operation of multiple building clusters. Each scenario runs 100 rounds of experiments to collect three indicators: energy efficiency compliance rate, average response delay, and system stability score.

Table 6：Performance of models under typical complex climate scenarios

Test Scenario	Energy Efficiency Compliance Rate (%)	Average Response Delay (s)	Stability Score (10)
Extreme High Temperature in Summer	93.1	2.4	9.2
Low Temperature Heating in Winter	90.6	2.7	8.8
Sharp Fluctuations in Electricity Price	91.8	2.6	8.9
High-Concurrency in Multi-Building Groups	89.4	3.1	8.6

As shown in Table 6, under extreme high temperatures in summer, the model utilizes a combination of prediction and regulation to achieve rapid allocation of cold sources, with an energy efficiency compliance rate of up to 93.1% and an average response time of only 2.4 seconds, demonstrating high adaptability to extreme cooling loads; Under the condition of "low-temperature heating in winter", the system maintains continuous operation by optimizing the heating strategy, with an energy efficiency compliance rate of 90.6% and a stability score of 8.8, reflecting its stability in peak energy consumption; In the context of severe fluctuations in electricity prices, the model dynamically balances comfort and cost through a demand response mechanism, with an energy efficiency compliance rate of 91.8% and a delay of 2.6 seconds, demonstrating its flexibility in market disturbances; In the context of "high concurrency in multiple building clusters", the system effectively alleviates conflicts through hierarchical regulation and resource sharing mechanisms, with an energy efficiency compliance rate of 89.4% and a stability score of 8.6, verifying its robustness in group collaboration scenarios.

The model maintains an energy efficiency compliance rate of over 89% and a response delay of less than 3.1 seconds under four complex operating conditions, with stability scores exceeding 8.5, demonstrating its good adaptability and robustness.

5.3 Feasibility assessment of system resource expenditure and building scene deployment

In the energy efficiency control of green buildings in hot summer and cold winter zones, the implementation of the model not only depends on the accuracy of prediction and optimization, but also on the adaptability of computing resources, communication bandwidth, and operating platforms. This study evaluated the resource cost and deployment feasibility of an energy efficiency control model that integrates artificial intelligence optimization algorithms in typical building clusters.

The model includes three major modules: edge acquisition, center optimization, and interactive feedback. The edge acquisition module is deployed in building BAS or monitoring gateways for real-time acquisition of meteorological, indoor temperature and humidity, and equipment operation data. Under a 1-minute sampling period, the CPU usage of a single node remains within 30%, with a memory consumption of approximately 1GB. It can run stably on common embedded controllers without the need for high-performance hardware support. The central optimization module is based on GPU servers to complete energy consumption prediction and strategy generation, with an average control cycle of 2.3 seconds and optimization calculations accounting for about 65%. Taking mid-range GPUs (such as RTX A2000) as an example, they can support real-time control of over a hundred terminals and provide lightweight versions to adapt to resource constrained scenarios. The interactive feedback module transmits data and instructions through WebSocket, with a bandwidth requirement of approximately 3.9Mbps and a latency of less than 180ms, which can meet the real-time requirements of building group monitoring and support remote operation and maintenance. In terms of economic investment, taking a medium-sized building complex consisting of 5 office buildings, 300 rooms, and 500 collection points as an example, the total investment is about 800000 yuan, covering software, hardware, and platform integration, which is lower than most similar solutions. Modular design supports later expansion, compatible with BAS, EMS, and smart building platforms, avoids information silos, and has hot swappable and remote update capabilities. In addition, the model can seamlessly integrate with existing BAS, EMS, and smart building platforms through standard interfaces, avoiding information silos, supporting module hot plugging and remote updates, and significantly reducing later operation and maintenance costs. Overall, the model is feasible in terms of computational burden, economic investment, and compatibility, providing solid support for the promotion and application of energy efficiency management in green buildings in hot summer and cold winter zones.

5.4 The application value of models in improving energy efficiency of green buildings

In the energy efficiency optimization of green buildings in hot summer and cold winter zones, improving operational efficiency and ensuring system stability are the key to implementing energy efficiency management. The energy efficiency control model proposed in this study, which integrates artificial intelligence optimization algorithms, has demonstrated significant value in multiple application areas. From the perspective of operational performance, the model achieves dynamic updates and path corrections in energy consumption scheduling through deep integration of prediction and optimization, significantly improving energy utilization and operational efficiency. In the experimental environment, the regulation response time is shortened to less than 2 seconds on average, and the energy utilization rate is stable at more than 90%. At the same time, the closed-loop feedback mechanism can quickly distinguish the interference caused by electricity price fluctuations, equipment shutdowns, and sudden increases in demand, and reconstruct optimization strategies in a short period of time to avoid uncontrolled energy efficiency fluctuations. According to statistics, unplanned operational interruptions have decreased by about 40%, the success rate of demand response has increased to 93%, and energy waste and equipment overload have significantly decreased. In terms of energy efficiency management, the model visualizes energy consumption distribution, equipment status, and comfort indicators through a graphical platform, allowing operators to intuitively grasp the global status of the system and make decisions and trend judgments based on data. This model breaks through the traditional control method that relies on experience and promotes energy efficiency management to shift from passive regulation to active optimization. System compatibility also enhances its potential for promotion. The model can seamlessly integrate with BAS, EMS, and smart building systems, supporting remote deployment and modular expansion, and adapting to different types and sizes of building clusters. Its standardized interface avoids duplicate construction and information isolation issues, making the energy efficiency system more flexible in updates and operations, and reducing additional investment costs.

5.5 Comparison with state-of-the-art studies

Table 1 provides a reference for quantitative comparison.The proposed framework achieves a prediction MAE of 6.8%, energy utilization of 91.3%, average response delay of 1.9 s, and comfort compliance of 92.4%.In contrast, Boutahri et al. (2025) reported 14% energy saving without comfort control, Wei et al. (2017) achieved 15% saving in simulation, and Gao et al. (2019) obtained MAE 0.29 with 11% comfort gain. Ding et al. (2022) reached RMSE 0.32 and 13% saving, while later studies focused on single objectives or simulation only.Our method lowers prediction error, enhances comfort, and raises utilization in both simulation and field tests.Differences mainly stem from (i) larger and more diverse data (14 M records, two years), (ii) closed-loop integration of forecasting, demand response and optimization, (iii) inclusion of field deployment, and (iv) reward shaping on comfort and equipment life.Paired t-tests ($\alpha = 0.05$) across 30 runs confirm that gains in MAE, utilization and comfort are statistically significant.

6 Conclusion

This article proposes a comprehensive energy efficiency control model that integrates deep learning, reinforcement learning, and evolutionary optimization algorithms to address issues such as insufficient prediction accuracy, delayed dynamic response, and system instability in green building energy efficiency control in hot summer and cold winter zones. The model constructs a closed-loop framework of "prediction optimization execution feedback". The experimental results show that the model outperforms traditional methods in energy consumption prediction, demand response, energy utilization, and comfort maintenance. The prediction error is reduced to 6.8%, the energy utilization rate reaches 91.3%, the response delay is shortened to 1.9 seconds, the comfort compliance rate is 92.4%, and the interruption rate is only 3.5%. This verifies the adaptability and stability of the model in complex climates. At the same time, the model performs well in terms of computing resources and communication overhead, and can run stably in common building controllers and mid-range GPU environments, making it feasible for application in medium to large building clusters. However, there are still shortcomings in this study: firstly, the dataset size is limited and the scene diversity is insufficient, which needs to be further validated in a larger range of building clusters; Secondly, the convergence speed of reinforcement learning is slow and the training cost is high, which is not conducive to large-scale real-time deployment; Thirdly, the adaptability of cross building group collaboration and multi terminal integration operation still needs further research. Future research can be conducted from three aspects: firstly, introducing transfer learning and self supervised pre training mechanisms to enhance their applicability under different climates and building types; Second, combine edge computing, model compression and distributed optimization to reduce resource consumption and enhance real-time scheduling capability; The third is to expand cross scenario collaboration applications, promote the promotion of models in energy efficiency management of urban level building clusters, and assist in green and low-carbon development. In summary, the energy efficiency control framework proposed in this study provides an effective path for improving the energy efficiency of green buildings in hot summer and cold winter zones, and lays the engineering and theoretical foundation for the construction of intelligent control systems.

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