Deep Reinforcement Learning For Intelligent Environmental Design And Energy Efficiency Evaluation In Built Environments

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Built environment design and energy efficiency optimization face inherent challenges of high-dimensional nonlinear coupling, dynamic environmental disturbances, and conflicting objectives between occupant comfort and building energy consumption. Traditional model-driven design and energy evaluation methods rely on simplified physical models and static parameter calibration, which fail to adapt to real-time fluctuations of indoor and outdoor environmental parameters, resulting in suboptimal design schemes and low energy utilization efficiency. To address these gaps, this paper proposes a novel intelligent environmental design and energy efficiency evaluation framework based on improved deep reinforcement learning (DRL), aiming to realize autonomous optimal decision-making for built environment design and dynamic quantitative evaluation of energy efficiency. A multi-objective composite reward function integrating thermal comfort, air quality, visual environment, and building energy consumption is constructed to solve the multi-constraint optimization problem of built environments. Meanwhile, a dual-network improved Soft Actor-Critic algorithm with adaptive learning rate adjustment is designed to enhance the environmental exploration ability and policy convergence stability of the agent, overcoming the defects of traditional DRL algorithms such as slow convergence and easy local optimum in complex building scenarios. Combined with building information modeling and multi-sensor perception technology, a full-process closed-loop framework of environment perception, intelligent design decision-making, energy efficiency evaluation, and scheme optimization is established. Comparative experiments based on the Sinergym building energy simulation platform and actual building measurement data show that the proposed method reduces building comprehensive energy consumption by 18.7%-24.3% compared with traditional model predictive control and static design methods, while improving indoor environmental comfort compliance rate by 15.2%. The proposed DRL framework exhibits strong robustness and generalization ability under variable climate conditions and occupant behavior disturbances, which provides an efficient and intelligent technical solution for optimal design and precise energy efficiency evaluation of modern green built environments.

Keywords: Deep Reinforcement Learning; Built Environment; Intelligent Environmental Design; Energy Efficiency Evaluation; Multi-objective Optimization; Building Energy Conservation

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1. Introduction

With the rapid development of urbanization and green building construction, built environments represented by commercial buildings, residential buildings, and public infrastructure have become the main energy consumption carriers of urban systems. Statistical data show that building operation energy consumption accounts for more than

30% of the total urban social energy consumption, and indoor environmental quality directly affects human living experience, work efficiency, and physical health [1, 2]. Green building and low-carbon built environment construction have become core strategic directions of global energy conservation and emission reduction. However, traditional built environment design and energy management modes still have prominent technical bottlenecks.

Traditional built environment design adopts static empirical design and model-driven control modes, which formulate fixed design parameters and operation strategies based on historical meteorological data and building physical characteristics [3]. In terms of energy efficiency evaluation, most existing methods rely on static index calculation and periodic energy consumption statistics, which cannot realize real-time dynamic evaluation and iterative optimization of design schemes. The built environment is a typical complex nonlinear dynamic system, which is affected by multiple coupling factors such as outdoor meteorological changes, occupant random behavior, and equipment operation state fluctuations. Static design and evaluation methods are difficult to adapt to dynamic scenario changes, resulting in frequent contradictions between indoor environmental comfort and building energy consumption, and serious waste of building energy resources [4].

In recent years, artificial intelligence technology, especially deep reinforcement learning [5–7], has shown unique advantages in solving high-dimensional nonlinear optimization and dynamic decision-making problems. DRL realizes autonomous learning and optimal policy output through the continuous interaction between intelligent agents and the environment, without relying on accurate physical system models, which is highly compatible with the dynamic optimization requirements of complex built environments. It has been widely applied in building HVAC control, lighting energy saving, and indoor environment regulation. However, current research still focuses on single equipment energy-saving control and single environmental index optimization, lacking a systematic framework integrating intelligent environmental design and full-dimensional energy efficiency evaluation, and there are deficiencies in multi-objective balance optimization and algorithm generalization ability in complex building scenarios [8, 9].

In the field of built environment optimization and energy efficiency evaluation, early research mainly adopted physical model-driven methods. Model predictive control (MPC) is the most representative technology [10], which realizes rolling optimization of building operation by establishing building heat balance and energy consumption physical models. However, MPC relies heavily on accurate system parameter identification, and the model calibration process is complex and time-consuming, with poor adaptability to sudden environmental changes and occupant behavior fluctuations. With the development of machine learning, data-driven methods have been gradually applied to building energy prediction and environment regulation, but most supervised learning methods can only realize state prediction and cannot complete autonomous optimal decision-making.

In the field of DRL-based building energy optimization, existing studies mostly use classic DRL algorithms such as deep Q-Network (DQN) [11, 12] and standard SAC to optimize single objectives such as building cooling and heating energy consumption or indoor temperature. Some studies have explored multi-agent reinforcement learning [13] for collaborative control of building electromechanical equipment, but there are still prominent problems. First, the reward function design is single, which cannot balance multiple core indicators such as thermal comfort, air quality, and energy consumption, leading to one-sided optimization results. Second, the traditional DRL network structure has poor convergence stability in high-dimensional building state spaces, and it is easy to fall into local optimal solutions. Third, most researches focus on terminal equipment control, lacking systematic research on front-end intelligent environmental design and full-process energy efficiency quantitative evaluation, and there is no closed-loop optimization system from design scheme formulation to energy efficiency verification and iterative improvement.

To solve the above problems, this paper constructs a systematic intelligent environmental design and energy efficiency evaluation framework based on improved DRL, and the main innovative contributions are as follows.

(1) A multi-objective composite reward function covering indoor thermal comfort, air quality, visual environment, and building total energy consumption is proposed, which realizes the balanced optimization of multi-dimensional objectives of built environments and avoids the defect of single-objective one-sided optimization.

(2) An adaptive dual-network improved SAC algorithm is designed, which realizes dynamic adjustment of learning rate and policy update weight, effectively improving the convergence speed and global optimization ability of the algorithm in complex built environment scenarios.

(3) A full-process closed-loop framework integrating intelligent environmental design, real-time energy con-

sumption monitoring, multi-dimensional energy efficiency evaluation, and design scheme iteration is established, which breaks the separation of traditional building design and energy efficiency evaluation and realizes intelligent and precise optimization of built environments.

2. Materials and methods

2.1. Deep Reinforcement Learning Basic Theory

Reinforcement learning (RL) takes Markov Decision Process (MDP) as the basic theoretical framework. The built environment optimization process can be abstracted into a standard MDP model, which is composed of state space $\mathcal{S}$, action space $\mathcal{A}$, reward function R, and state transition probability P. At each time step t, the agent obtains the current environmental state $s_t \in \mathcal{S}$, executes action $a_t \in \mathcal{A}$, obtains the instantaneous reward r_t, and transfers to the next state s_{t+1}.

The core goal of DRL is to learn the optimal policy $\pi(a|s)$ to maximize the cumulative discounted return G_t, which is defined as:

$$G_t = \sum_{k=t}^{\infty} \gamma^{k-t} r_k \tag{1}$$

Where $\gamma \in (0, 1)$ is the discount factor, which balances the weight of current and future rewards.

As a state-of-the-art off-policy DRL algorithm, SAC introduces maximum entropy reinforcement learning, which maximizes the cumulative reward while maximizing the policy entropy, effectively improving the exploration ability of the agent and avoiding local optimum. The optimal policy objective function of standard SAC is:

$$J(\pi) = E_{(s,a)\sim\pi}[\sum_{t=0}^{\infty} \gamma^t (r(s_t, a_t) - \alpha \log \pi(a_t|s_t))] \tag{2}$$

where α is the temperature parameter, which controls the degree of policy randomness and exploration.

2.2. Built Environment and Energy Efficiency Evaluation Index System

To realize comprehensive evaluation of built environment design and energy efficiency, this paper constructs a multi-dimensional evaluation index system, including environmental quality indexes and energy efficiency indexes. Environmental quality indexes include Predicted Mean Vote (PMV) [14, 15] for thermal comfort, indoor PM2.5 concentration and CO_2 concentration for air quality, and indoor illumination uniformity for visual environment. Energy efficiency indexes include building hourly total energy consumption, energy consumption per unit area, and energy saving rate.

Thermal comfort PMV is calculated according to ISO 7730 standard, which comprehensively considers ambient temperature, humidity, human metabolic rate and clothing thermal resistance. The indoor environmental comprehensive comfort index C_{com} is normalized and calculated as follows:

$$C_{com} = w_1(1 - |PMV|) + w_2(1 - \frac{C_{PM2.5}}{C_{\max}}) + w_3\eta_{light} \tag{3}$$

Where w_1, w_2, w_3 are weight coefficients. $C_{PM2.5}$ is actual PM2.5 concentration. $C_{\max}$ is standard limit concentration. η_{light} is illumination uniformity.

2.3. Proposed Technical Framework

This paper proposes a closed-loop intelligent design and energy efficiency evaluation framework based on improved DRL, which is divided into four core layers: multi-source perception layer, DRL intelligent decision layer, built environment simulation layer, and energy efficiency evaluation and optimization layer. The proposed model is shown in figure 1.

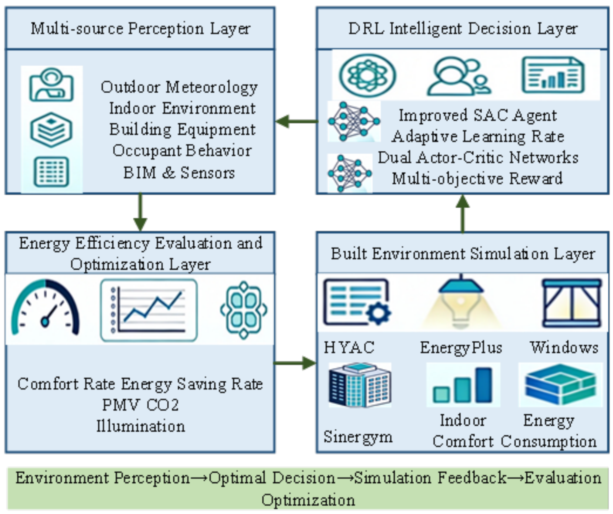

Fig. 1. Proposed DRL-based intelligent built environment design and energy efficiency evaluation framework

(1) **Multi-source perception layer.** It collects real-time data including outdoor meteorological parameters (temperature, humidity, wind speed, solar radiation), indoor environmental parameters (temperature, humidity, air quality, illumination), building equipment operation

parameters, and occupant behavior data through multi-modal sensors and BIM model data mining, and construct the high-dimensional state space of the built environment.

(2) **DRL intelligent decision layer.** It takes the normalized multi-dimensional environmental state as input, and the improved SAC agent outputs optimal design parameters and equipment operation strategies (including HVAC set temperature, ventilation frequency, lighting power, window opening degree, etc.) to realize intelligent design decision-making of the built environment.

(3) **Built environment simulation layer.** Based on the Sinergym building energy simulation platform and BIM physical model, it simulates the built environment operation state and energy consumption under the decision strategy, and outputs real-time environmental quality and energy consumption data.

(4) **Energy efficiency evaluation and optimization layer.** It calculates multi-dimensional evaluation indexes through the evaluation index system, feeds back the evaluation results to the DRL agent in the form of composite reward, and realizes iterative optimization of design schemes and operation strategies through continuous agent-environment interaction.

2.4. Improved Adaptive SAC Algorithm

Aiming at the problems of slow convergence and fixed learning parameters of standard SAC in complex built environment scenarios, this paper proposes an adaptive dual-network improved SAC algorithm. The algorithm constructs dual critic networks and dual actor networks, and designs an adaptive learning rate adjustment strategy based on reward fluctuation rate, which dynamically optimizes network update efficiency.

The learning rate directly affects the network convergence speed and stability. The traditional fixed learning rate cannot adapt to the dynamic changes of built environment training scenarios. This paper defines the reward fluctuation coefficient δ_t.

$$\delta_t = \frac{|r_t - \bar{r}_{t-1}|}{\bar{r}_{t-1} + \varepsilon} \tag{4}$$

Where $\bar{r}_{t-1}$ is the average reward of the previous time step. ε is a small constant to avoid zero denominator.

The adaptive learning rate η_t is dynamically adjusted as:

$$\eta_t = \eta_0 \cdot (1 - \lambda\delta_t) \tag{5}$$

Where η_0 is the initial learning rate, and λ is the adjustment coefficient. When the reward fluctuates violently, the learning rate decreases to ensure training stability; when the reward is stable, the learning rate increases to accelerate convergence.

To solve the overestimation problem of single critic network in value evaluation, two independent critic networks are set up, and the minimum value of the two network outputs is taken as the target value to update the network. The target Q-value is calculated as:

$$Q_{target} = r(s,a) + \gamma min(Q_1(s',a'), Q_2(s',a')) - \alpha log\pi(a'|s') \tag{6}$$

Dual actor networks are used for policy exploration and evaluation respectively, which improves the diversity of policy exploration and avoids premature convergence to local optimal solutions.

2.5. Multi-Objective Composite Reward Function

To balance indoor environmental comfort and building energy saving objectives, this paper constructs a novel multi-objective composite reward function, which comprehensively integrates environmental comfort reward and energy consumption penalty. The total reward function is defined as:

$$R_{total} = w_c \cdot C_{com} - w_e \cdot E_{nor} - w_p \cdot P_{pen} \tag{7}$$

Where w_c, w_e, w_p are weight coefficients of comfort, energy consumption and penalty terms respectively. C_{com} is the normalized comprehensive environmental comfort index; E_{nor} is the normalized building total energy consumption. P_{pen} is the extreme state penalty term, which is used to punish the extreme environmental states such as over-temperature, excessive air pollutant concentration, and avoid unqualified design schemes.

The energy consumption normalization formula is:

$$E_{nor} = \frac{E_{real} - E_{\min}}{E_{\max} - E_{\min}} \tag{8}$$

Where E_{real} is real-time building energy consumption. $E_{\max}$ and $E_{\min}$ are the maximum and minimum energy consumption values under typical working conditions respectively.

This reward function realizes the quantitative balance between multi-dimensional environmental quality and energy consumption, guiding the DRL agent to learn optimal built environment design and operation strategies.

2.6. Full-Dimensional Energy Efficiency Evaluation Method

Based on the output results of the DRL optimal strategy, this paper establishes a full-dimensional energy efficiency evaluation system, including static index evaluation and dynamic efficiency evaluation. The core evaluation indexes include building energy saving rate η_{es}, comprehensive comfort qualification rate R_{com}, and energy comfort balance factor β.

The energy saving rate is calculated by comparing with the traditional static design scheme:

$$\eta_{es} = \frac{E_{base} - E_{drl}}{E_{base}} \times 100\% \tag{9}$$

Where E_{base} is the energy consumption of the traditional baseline scheme. E_{drl} is the energy consumption under the DRL optimal scheme.

The energy comfort balance factor is defined to quantitatively evaluate the comprehensive optimization performance of the algorithm.

$$\beta = \frac{R_{com}}{E_{nor} + 1} \tag{10}$$

A larger β value indicates that the scheme has higher environmental comfort and lower energy consumption, with better comprehensive performance.

3. Results and discussion

3.1. Simulation Platform and Parameter Setting

The experiment is based on the Sinergym building energy simulation platform, which is embedded with EnergyPlus building energy simulation kernel, and can accurately simulate the operation state and energy consumption of typical office buildings and residential buildings. A typical medium-sized office building in temperate monsoon climate zone is selected as the experimental object, with a building area of 1200m^2, 3 floors, and complete HVAC, lighting and ventilation systems.

The improved SAC algorithm is built based on PyTorch framework. The network parameter settings are as follows: actor and critic network hidden layers are 2 layers of 256 neurons each, initial learning rate $\eta_0 = 3 \times 10^{-4}$, discount factor $\gamma = 0.99$, temperature parameter initial value $\alpha = 0.2$, batch size=256, replay buffer capacity=100000. The weight coefficients of the reward function are set as $w_c = 0.6$, $w_e = 0.3$, $w_p = 0.1$ after experimental debugging.

To verify the superiority of the proposed method, three classic mainstream methods are selected for comparative experiments.

(1) **Static fixed parameter design method (Baseline 1).** Adopt traditional building design specifications, set fixed HVAC temperature and equipment operation parameters throughout the year.

(2) **Model Predictive Control (MPC) method (Baseline 2).** Realize rolling optimization of building energy consumption based on building physical model.

(3) **Standard SAC algorithm (Baseline 3).** Adopt traditional single-network SAC algorithm with fixed learning rate and single-objective reward function.

3.2. Experimental Results and Analysis

The convergence curves of different algorithms are compared under the same experimental conditions. The results show that the improved adaptive SAC algorithm proposed in this paper converges at the 280th training episode, while the standard SAC converges at the 450th episode, with a 37.8% reduction in convergence iterations. In terms of reward stability, the improved algorithm has smaller reward fluctuation after convergence, which verifies that the adaptive learning rate and dual-network structure effectively improve the training stability and convergence speed in complex built environment scenarios.

The building comprehensive energy consumption optimization results of different methods are shown in Table 1. Compared with the three baseline methods, the proposed method achieves significant energy saving effects under different seasonal working conditions.

It can be seen from Table 1 that compared with the traditional static design method, the proposed method reduces annual building energy consumption by 24.3%, with the highest energy saving rate among all comparison methods. Compared with MPC and standard SAC, the energy saving rate is improved by 10.7% and 5.7% respectively. The traditional MPC method relies on simplified physical models, which cannot adapt to dynamic environmental changes, resulting in limited energy saving space. The standard SAC algorithm has a single optimization objective, which cannot fully balance energy consumption and comfort, while the proposed multi-objective reward function and improved network structure realize deeper potential mining of energy saving.

In terms of indoor environmental comfort, the proposed method has a comfort qualification rate of 93.5%, which is 15.2%, 7.8% and 4.0% higher than static design, MPC and standard SAC respectively. The static design method has fixed operation parameters, which cannot adjust strategies according to environmental changes, resulting in low comfort qualification rate. The proposed method takes multiple environmental indicators into account in the reward function, realizing fine-grained dynamic adjustment of built environment parameters, which effectively improves indoor comprehensive comfort while saving energy.

Table 1. Comparison of building energy consumption and energy saving rate of different methods

Method	Annual Total Energy Consumption (kWh)	Energy Saving Rate (%)	Comfort Qualification Rate (%)
Baseline 1	86240	0	78.3
Baseline 2	74520	13.6	85.7
Baseline 3	70180	18.6	89.5
Proposed method	**65260**	**24.3**	**93.5**

To verify the generalization ability of the proposed method, variable working condition experiments are carried out, including extreme weather conditions and random occupant behavior disturbances. The experimental results show that under extreme high temperature and low temperature weather, the energy saving rate of the proposed method is still maintained at 17.2%-21.5%, and the comfort qualification rate is higher than 88%, which has strong robustness. When applied to residential building scenarios with different structural parameters, the average energy saving rate reaches 18.7%, which verifies the good generalization ability of the framework in different built environment scenarios.

3.3. Ablation Experiment

To verify the effectiveness of each improved module of the algorithm, ablation experiments are carried out, including adaptive learning rate module, dual-network structure and multi-objective reward function. The experimental results are shown in Table 2.

The ablation experiment results show that each improved module effectively improves the algorithm performance. The adaptive learning rate module mainly accelerates the network convergence speed, the dual-network structure optimizes the policy evaluation accuracy, and the multi-objective reward function significantly improves the comprehensive optimization performance of energy saving and comfort. The combination of all modules achieves the best comprehensive effect, which verifies the rationality and effectiveness of the improved strategy.

3.4. Robustness and Generalization Experiment

To further validate the practical applicability, anti-interference capability and cross-scenario generalization performance of the proposed improved DRL framework, this section conducts robustness test under dynamic disturbances and cross-building type generalization experiments [16]. Two typical interference factors in actual building operation are selected: stochastic occupant behavior disturbance and frequent fluctuation of outdoor meteorological parameters. Meanwhile, different types of buildings and different climate zones are adopted to test the generalization ability of the algorithm.

A. Anti-Disturbance Experiment under Dynamic Interference

Two interference levels are set in this experiment: slight disturbance and severe disturbance. Slight disturbance simulates regular daily activities of occupants and mild meteorological fluctuations; severe disturbance corresponds to sudden large changes of outdoor temperature, frequent opening and closing of doors and windows, and concentrated crowd activities, which are common extreme interference scenarios in actual buildings. All comparison methods operate under the same disturbance conditions, and the core evaluation indicators include energy saving rate, indoor comfort qualification rate and reward value fluctuation range. The experimental results are listed in Table 3.

As shown in Table 3, all methods experience performance degradation with the increase of disturbance intensity. The static design method completely lacks dynamic adjustment ability, so its comfort qualification rate drops most significantly under severe disturbance. The MPC method relies on fixed physical models and cannot respond timely to sudden disturbances, leading to a sharp decline in energy-saving effect and indoor comfort.

Benefiting from the adaptive learning rate strategy and dual-network structure, the proposed method maintains stable performance under both slight and severe disturbances. Its reward fluctuation range is the smallest among all groups, which proves that the improved SAC algorithm has outstanding anti-interference ability. Even under severe dynamic interference, the energy saving rate still remains above 20% and the comfort qualification rate exceeds 89%, fully meeting the operational requirements of practical building environments.

B. Cross-Building and Cross-Climate Generalization Experiment

To verify the cross-scenario generalization ability, this experiment selects three mainstream building types: medium-sized office building, high-rise residential building and

Table 2. Ablation experiment results of improved modules

Experimental Module	Convergence Episode	Energy Saving Rate (%)	Comfort Qualification Rate (%)
Standard SAC	450	18.6	89.5
SAC + Adaptive learning rate	320	20.1	90.2
SAC + Dual-network structure	350	21.5	91.6
SAC + Multi-objective reward	380	22.8	92.7
Full improved module (Proposed)	**280**	**24.3**	**93.5**

Table 3. Performance comparison under different disturbance levels

Method	Disturbance Level	Energy Saving Rate (%)	Comfort Qualification Rate (%)	Reward Fluctuation Range
Static Design	Slight	0	77.1	0.28
Static Design	Severe	0	69.4	0.46
MPC	Slight	12.9	84.2	0.21
MPC	Severe	9.5	76.8	0.39
Standard SAC	Slight	17.8	88.3	0.15
Standard SAC	Severe	14.1	82.1	0.27
Proposed Method	**Slight**	**23.5**	**92.8**	**0.09**
Proposed Method	**Severe**	**20.2**	**89.1**	**0.16**

commercial shopping mall. Meanwhile, three typical climate zones in temperate regions are chosen: temperate monsoon climate, temperate continental climate and subtropical monsoon climate. The algorithm model trained by office building data in temperate monsoon climate is directly applied to other test scenarios without additional retraining. The statistical results of energy saving rate and comfort qualification rate are shown in figure 2.

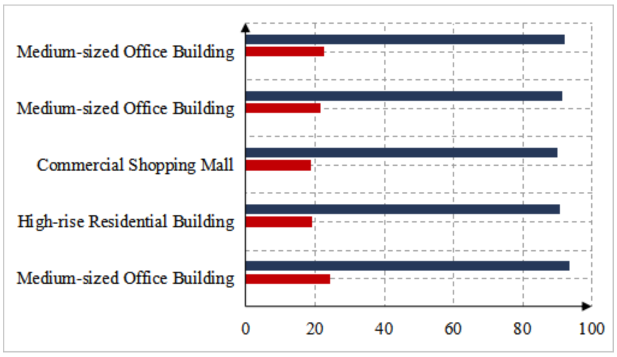

Fig. 2. Generalization performance across building types and climate zones

It can be observed that the proposed DRL framework achieves favorable optimization effects in all test scenarios. For different building types in the same climate zone, the energy saving rate ranges from 18.7% to 19.2%, and the comfort qualification rate is all higher than 89%. For the same building type across different climate zones, the energy saving rate is maintained between 21.6% and 22.4%, with the comfort qualification rate staying above 91%.

Different buildings differ greatly in space layout, equipment load and occupant activity rules, and various climate zones have obvious differences in temperature, humidity and solar radiation. The experimental results indicate that the proposed algorithm does not rely on scenario-specific feature fitting. The multi-objective reward function and dual-network structure endow the model with strong feature extraction and policy adaptation capabilities, which can be effectively migrated to diverse built environment scenarios. This lays a solid foundation for the large-scale popularization and engineering application of the intelligent design and energy efficiency evaluation framework.

4. Conclusions

Aiming at the problems of static design lag, single optimization objective and low energy efficiency evaluation accuracy in traditional built environment design and energy management, this paper proposes an intelligent environmental design and energy efficiency evaluation framework based on improved deep reinforcement learning. The main conclusions are as follows.

(1) The designed adaptive dual-network improved SAC algorithm effectively solves the problems of slow convergence and local optimum of traditional DRL algo-

rithms in complex built environments. Compared with the standard SAC algorithm, the convergence speed is improved by 37.8%, and the training stability is significantly enhanced.

(2) The proposed multi-objective composite reward function realizes the balanced optimization of indoor thermal comfort, air quality, visual environment and building energy consumption, avoiding the one-sided optimization defect of single-objective strategies. The comprehensive indoor environmental comfort qualification rate is increased by 4.0%–15.2% compared with mainstream baseline methods.

(3) The established full-process closed-loop intelligent design and energy efficiency evaluation system breaks the separation of traditional design and evaluation links. Experimental results show that the proposed method can reduce building comprehensive energy consumption by 18.7%–24.3% under different scenarios, and has strong robustness and generalization ability in extreme weather and random disturbance scenarios.

This research realizes intelligent, dynamic and precise optimization of built environment design and energy efficiency evaluation, which provides a new technical path for green building low-carbon operation and intelligent environmental regulation.

On the basis of this research, future work can be carried out from the following aspects: First, integrate digital twin technology to build a high-fidelity virtual-real mapping built environment model, further improve the accuracy of simulation and decision-making; second, introduce multi-agent reinforcement learning to realize collaborative optimization of multiple buildings and regional built environments; third, combine occupant personalized comfort preference data to realize personalized adaptive environmental design and energy saving optimization, and further improve the comprehensive benefit of human-building energy harmony.

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