The Comfort Assessment of Indoor Environment Using Reinforcement Learning

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Abstract. With the continuous development of CAD technology, the indoor environment comfort evaluation system based on the CAD model is also constantly improved and has been widely used. In this paper, the indoor environment comfort evaluation system based on the CAD model is studied by introducing a reinforcement learning strategy. According to different indoor environment comfort evaluation systems, different state spaces, decision spaces, reward functions, and learning algorithms are analyzed. The reinforcement learning theory is applied to the indoor environment comfort evaluation system based on the results of the above analysis. Firstly, through the introduction and analysis of the reinforcement learning theory, reinforcement learning algorithm, and indoor environment comfort evaluation system, the application results are analyzed, and finally, relevant confirmatory experiments are designed. The experimental results show that the CAD model based on reinforcement learning can evaluate indoor environment comfort, which is highly reliable and can provide a scientific basis for indoor environment comfort evaluation.

Keywords: Reinforcement Learning; Indoor Environment; Comfort Evaluation; CAD Mode
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1 INTRODUCTION

In the field of contemporary architecture, the comfort assessment of the interior environment has become an indispensable part of the design and planning process. With the development of science and technology, traditional evaluation methods are gradually being replaced by intelligent and automated technologies. Reinforcement learning, as an advanced machine learning technique, has shown excellent performance and potential in many fields [1]. Especially in the indoor environment comfort evaluation, the application of reinforcement learning can not only improve the accuracy and efficiency of the evaluation but also provide designers with more intuitive and dynamic feedback to optimize the design scheme. The purpose of this study is to explore the application of reinforcement learning (CAD) in indoor environment comfort assessment. By combining reinforcement learning algorithm and CAD technology, this study attempts to build an intelligent system that can automatically learn and predict the comfort of the indoor environment, and then provide real-time adjustment suggestions for designers [2]. The application of this system is expected to achieve effective control of indoor environment comfort at the early stage of architectural design and reduce the cost and time of later adjustment. Indoor environment comfort is a multi-dimensional concept, it involves temperature, humidity, light, noise and other factors [3]. Traditional evaluation methods often rely on static simulation and subjective judgment, which limits the accuracy and comprehensiveness of evaluation to some extent. The reinforcement learning algorithm can dynamically adjust the strategy to achieve the optimal indoor environment configuration through interactive learning with the environment. In the CAD environment, this means that the system can automatically adjust the design solution based on real-time data and design parameters to achieve the best comfort standards. With the continuous improvement of the indoor environment comfort evaluation system, the indoor environment comfort evaluation system based on the CAD model has become a trend [4]. The traditional indoor environment comfort evaluation method has great limitations and cannot accurately evaluate indoor environment comfort, so it must be improved. In this context, scholars have begun to apply reinforcement learning theory to indoor environment comfort assessment systems and have achieved good results. In recent years, since reinforcement learning theory has achieved good results in practical application, scholars have begun to try to apply it to indoor environment comfort assessment systems. At present, domestic and foreign scholars have designed some indoor environment comfort assessment systems based on reinforcement learning theory, but most of these systems are developed in a specific field and are not adaptable to different fields [5].

With the continuous development of smart grid technology, smart home systems have become an indispensable part of it. Through efficient demand-side management strategies, not only can household electricity consumption be effectively reduced, but energy utilization efficiency can also be significantly improved. At the same time, with the increasing demand for quality of life, indoor environmental comfort has become another important aspect of concern for smart home systems. In CAD applications, reinforcement learning can assist designers in building more intelligent and efficient building models. Therefore, the application of intelligent edge analysis technology is particularly important, as it can process and analyze data in real-time on IoT terminal devices, thereby achieving real-time optimization of household energy use. However, as mentioned earlier, traditional cloud-centric data analysis services are inadequate in handling latency-sensitive user needs. For example, reinforcement learning algorithms can automatically adjust building design parameters by simulating the changes in indoor environmental parameters (such as temperature, humidity, lighting, etc.) under different design schemes and combining them with user comfort preference data. As an advanced AI technology, reinforcement learning simulates the trial-and-error learning process of intelligent agents in the environment, continuously optimizing their behavioral strategies to achieve specific goals and demonstrating great potential in indoor environment comfort evaluation and optimization [6]. Such as window size, sunshade position, air conditioning system configuration, etc., to maximize indoor environmental comfort while reducing energy consumption.

In the past decade, safety has not only been a core issue of continuous concern in the construction industry but indoor environmental comfort, as a key factor affecting the quality of living and work, has also been increasingly valued. Some scholars have conducted in-depth reviews of the research progress of these cutting-edge technologies and found that although the potential of DT in improving the safety of construction workers has been verified, its widespread application and simplification in actual construction still face many challenges. The dynamic and complex environment during the construction process not only increases safety risks but also limits the fine adjustment and optimization of indoor environment design [7]. Despite the efforts made by the construction industry to improve overall safety and interior environment design, the high casualty rate and unsatisfactory indoor comfort remain two major challenges. In this context, the rapid development of digital technology, especially the combination of digital twins (DT) and reinforcement learning (RL), has brought new opportunities to improve the health, safety, and indoor comfort of the construction industry. The application of reinforcement learning in CAD (Computer Aided Design) enables the design of indoor environments to be dynamically adjusted based on user preferences and real-time data to achieve optimal comfort. Digital twins can identify potential risks during the construction process in advance and optimize safety plans through high-precision simulation and prediction. Similarly, when reinforcement learning is used for indoor environment comfort evaluation in CAD, although it can significantly improve design efficiency and effectiveness, its model complexity, data requirements, and real-time response capability are also urgent issues that need to be addressed [8].

Realizing secure, private, and efficient communication in the field of the Internet of Things (IoT) faces enormous challenges, especially considering the massive growth and widespread application of IoT devices, such as smart home systems. Traditional blockchain solutions often come with high computational costs and time delays, which limit their potential for application in resource-constrained IoT environments. In recent years, blockchain technology has been widely researched and applied to enhance the security and privacy protection of the Internet of Things due to its decentralized nature and powerful data security protection capabilities. Specifically, the solution first constructs a blockchain-based smart home architecture that has been carefully designed to ensure high reliability in key security objectives such as privacy protection, data integrity, and system accessibility. This scheme not only enhances the security and privacy of the Internet of Things but also cleverly integrates the application of reinforcement learning in CAD (computer-aided design) for indoor environment comfort evaluation [9]. This comprehensive method aims to achieve a dual improvement in safety and comfort in smart home environments by intelligently allocating computing resources, optimizing data processing flows, and introducing efficient algorithms such as deep extreme learning machines (DELM). Furthermore, by combining reinforcement learning with blockchain technology, it is not only possible to incorporate users' long-term preferences for comfort during the CAD design phase. In order to overcome this obstacle and meet the current demand for indoor environment comfort evaluation, this article proposes an innovative and resource-efficient blockchain solution. At the same time, we use reinforcement learning algorithms to optimize indoor environment design in CAD systems. By simulating the changes in user comfort under different design schemes, we automatically adjust the indoor temperature, humidity, lighting and other parameters to achieve personalized and efficient indoor environment comfort. It can also monitor and adjust environmental parameters in real-time during the operation of smart homes, ensuring that the system can automatically optimize based on user feedback, thereby improving the living experience [10].

In order to solve this problem, reinforcement learning theory and CAD model are applied to the indoor environment comfort evaluation system, and the application results are analyzed and summarized. At the same time, in order to verify the effectiveness and feasibility of the indoor environment comfort evaluation system based on reinforcement learning theory, this paper also designed related experiments to verify the reliability and practical application value of the indoor environment comfort evaluation system based on reinforcement learning theory proposed in this paper.

2 RESEARCH STATUS

As early as the 1980s, foreign scholars began to study the evaluation system of indoor environmental comfort, mainly combining theory with simulation. At present, Nicoletti et al. [11] first conduct a systematic analysis of the human body and environment, establish corresponding CAD models and simulate them, then compare the simulation results with actual measurement data, and finally obtain the comfort evaluation results. Through research and investigation, some scholars have found that the establishment of this system requires a certain amount of experience, which is limited in practical measurement. Therefore, it is necessary to adopt an experience-based evaluation method. Research by some domestic scholars has shown that typical evaluation methods generally consist of two parts: the first part is a parameterized simulation model, the second part is the experience database. Foreign scholars generally divide indoor environmental comfort evaluation systems into two categories: one is based on traditional evaluation systems, and the second is an evaluation system based on computer simulation. These two systems have great research value in their respective fields.

With the continuous improvement of the Chinese economy, people's living standards have also significantly improved. However, China's research in this field started relatively late, mainly focusing on the application and scientific research in the field of built environments. Therefore, people have put forward higher requirements for the living environment and have begun to try to replace traditional indoor environment comfort evaluation methods with computer simulations. Through in-depth research and experiments, Parn and Edwards [12] have developed a series of models that can accurately evaluate human thermal comfort. These models have achieved good results in practical applications, providing important scientific basis and technical support for China's environmental design and urban planning fields. In addition, in-depth discussions were conducted on the construction of a thermal comfort evaluation model. They not only focus on comfort in static environments but also on the impact of dynamic changes in indoor air temperature, humidity, and other parameters on human perception. The continuous improvement and refinement of these models aim to provide more accurate evaluation criteria, thereby creating more suitable indoor thermal environments for people under different climatic conditions. Researchers from multiple disciplines are constantly innovating. They applied fuzzy control theory to indoor environmental quality evaluation. These scholars not only conducted in-depth research on the impact mechanism of indoor air humidity, temperature, ventilation, and other factors on human comfort but also developed a scientific indoor environment comfort evaluation system that can comprehensively consider multiple variables. Provide more accurate and comprehensive environmental assessments. Pepe and Costantino [13] have also conducted extensive research in this area. For example, in the field of building environment research, many scholars have proposed systems that use temperature prediction models to evaluate indoor environmental comfort.

By accurately predicting indoor temperature changes, these systems provide decision-makers with an effective indoor air quality analysis tool to ensure the comfort and health safety of living and working environments. Other scholars have proposed an indoor environment comfort evaluation system based on a dynamic human thermal sensation model. Domestic scholars have also conducted extensive research in this area. For example, some scholars have proposed an indoor environment comfort evaluation system based on fuzzy inference models, and Rasmussen et al. [14] proposed an indoor environment comfort evaluation system based on artificial neural networks and genetic algorithms. In the current research field, some academic researchers are constantly exploring and committed to developing more accurate and efficient methods for assessing indoor environmental comfort. They innovatively combined grey relational analysis and genetic algorithms to design and implement a comprehensive evaluation model. This method not only considers objective data information but also fully utilizes the intelligent characteristics of the algorithm, making indoor environment comfort evaluation more scientific and reasonable and has high practical value. At the forefront of academic research, researchers have proposed an innovative solution. By combining the powerful modelling ability of neural networks with the optimization performance of genetic algorithms, they developed a comprehensive indoor environment comfort evaluation system. This system can comprehensively and meticulously analyze and evaluate the impact of the indoor environment on people's comfort and provide scientific and reasonable suggestions for improvement.

In the AECOO (Architecture, Engineering, Construction, Owner, and Operations) industry, traditional methods of exchanging building models are gradually being replaced by more advanced information-sharing mechanisms, with Building Information Modeling (BIM) methods being particularly prominent. In this context, the World Wide Web Consortium Link Building Data Community Organization (W3C LBD-CG) proposed the Link Data Model and Best Practices. It not only provides a detailed description of the topology of the building, including the complex relationships between floors, spaces, and internal building elements, but also integrates a network-friendly 3D model for easy visualization and interaction of information. BIM not only advocates the use of digital technology to facilitate seamless information exchange among stakeholders but also strives to achieve comprehensive integration and dynamic updates of information. As BIM maturity moves towards level 3, a vision is gradually becoming clear: to achieve interdisciplinary, interoperable, distributed, and network-based real-time information exchange throughout the entire lifecycle of buildings to optimize decision-making processes and improve project efficiency. Specifically, when Yeung et al. [15] combined BOT with reinforcement learning in CAD (Computer Aided Design) for indoor environment comfort assessment, a completely new application scenario emerged: reinforcement learning algorithms can automatically adjust design parameters and optimize indoor environment layout and equipment configuration based on user comfort preferences, environmental parameters (such as temperature, humidity, and lighting), and real-time sensor data. By using BOT as a bridge for data exchange, reinforcement learning models can be seamlessly integrated into BIM environments to obtain accurate building topology information and spatial data, thereby achieving more precise environmental simulation and comfort assessment. The actual operational data collected by IoT devices, such as indoor temperature and humidity, air quality, etc., is fed back to the reinforcement learning system through the standardized interface of BOT, forming a closed-loop optimization mechanism. This lays a solid foundation for modern network applications to achieve the BIM maturity level 3 vision. To further enhance this capability, it introduces Building Topology Ontology (BOT) as the core vocabulary. In practical applications, BOT not only supports efficient iteration and optimization of reinforcement learning models in CAD systems but also promotes deep integration with Internet of Things (IoT) devices. This mechanism ensures the continuous optimization and adjustment of design schemes to adapt to the constantly changing needs in practical use. Based on the above research status at home and abroad, it can be seen that in the current relevant research, few scholars have combined and trained the CAD model and reinforcement learning and then applied it to the assessment of indoor environment comfort. Therefore, it is of great practical and academic significance to carry out research in this area.

3 DESIGN AND OPTIMIZATION OF A CAD MODEL EVALUATION SYSTEM

3.1 The Design Idea of CAD Model Evaluation System for Indoor Environment Comfort Based on Reinforcement Learning Strategy

At present, the common indoor environment is mainly based on the structure of the room layout and the innovation of space placement. Chinese decoration will improve the indoor environment and comfort of the owners who like Oriental, Chinese, and ancient charm, as shown in Figure 1.

Figure 1: Chinese style decoration of the interior environment comfort.

In order to evaluate the indoor environment's comfort objectively and quantitatively, this study designed a CAD model based on a reinforcement learning strategy. According to the actual evaluation requirements, in this system, we need to design a database containing different indoor environment comfort evaluation indicators and convert the data into numerical evaluation indicators through statistics of these indicators. Then, the comfort of the indoor environment is evaluated according to these evaluation indexes. In this process, it is necessary to build a CAD model based on a reinforcement learning strategy with the help of CAD software. The model includes a variety of evaluation systems corresponding to indoor environment comfort, and these evaluation systems are transformed into numerical evaluation indicators with correlation. Functions in CAD software are used to process these numerical evaluation indicators, and the obtained evaluation index data are input into the training model, and the training model is used to evaluate the indoor environment comfort. If this evaluation system is applied to the actual project, it can provide a scientific basis for the evaluation of indoor environment comfort. By combining the evaluation system with a reinforcement learning strategy, a high-accuracy evaluation of the evaluation system can be realized, and its schematic diagram is shown in Figure 2.

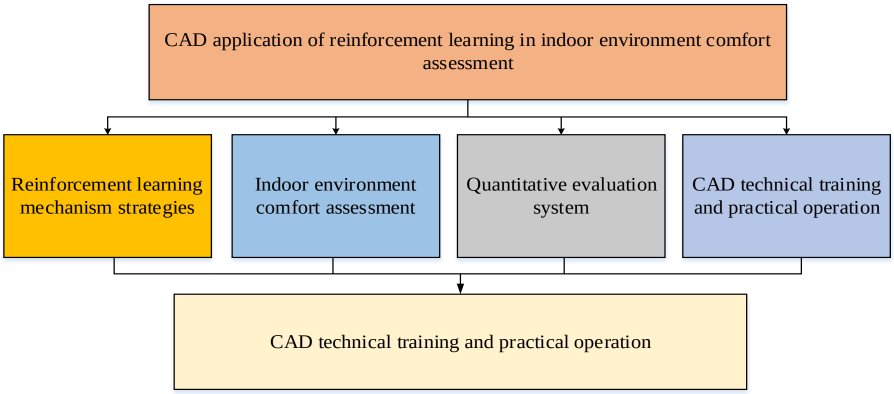


Figure 2: Reinforcement learning strategies based on CAD model in indoor environment comfort evaluation system.

As can be seen from Figure 2, in the indoor environment comfort evaluation system of CAD model based on reinforcement learning strategies, a variety of reinforcement learning strategies, CAD models, and evaluation functions constitute a systematic whole, and through their internal correlation cooperation, indoor environment comfort is evaluated. In this way, it can effectively avoid situations where the system has a greater degree of error in the process of evaluating comfort due to simple factors.

3.2 Operation Process Analysis of CAD Model Based on Reinforcement Learning Strategy in Indoor Environment Comfort Evaluation System

Based on the comfort assessment system in the above links, this study takes the specific unit type of a real estate product in a developer as an example. Its interior design and interior environment, as shown in Figure 3, are European style, which is quite different from the Chinese style in Figure 1 in terms of environmental comfort. This paper analyzes the operation process of a CAD model based on a reinforcement learning strategy in an indoor environment comfort evaluation system.

The specific steps of the CAD model based on reinforcement learning strategy in the operation process analysis of the indoor environment comfort evaluation system are as follows:

Step 1: To complete the indoor environment comfort assessment, it is necessary to construct an indoor environment comfort assessment model. Because of the indoor environment comfort evaluation system, it must be completed using CAD software to calculate quickly. Therefore, this paper uses VB6.0 to develop a CAD model based on reinforcement learning. Before the development, we must first learn the ActiveX control in VB6.0, and then create an interactive interface that can dynamically display the input variable (ActiveX attribute) and the output variable (ActiveX behaviour) of the user input.

Figure 3: European style decoration interior environment comfort.

The purpose of this is to enable users to carry out relevant operations on the computer very conveniently and complete the design of the indoor environment comfort assessment system. The corresponding reinforcement learning progressive function in this process is as follows:

$$W\ x\ = \int_{x_1}^{x_2} \Delta K_a - \Delta K_b\ dx - W_0 \tag{1}$$

Formula, ΔK_a and ΔK_b Respectively expressed in a and b The corresponding degree of reinforcement learning initialization under the two learning styles, W_0 Represents the initial value of the reinforcement learning optimization mechanism. After completing the progression of reinforcement learning, it is also necessary to set the reward function, whose expression is

$$g\ x\ = \frac{\sigma\ W(x) + c}{c + d} \tag{2}$$

The formula $W\ x$ Denotes the reinforcement learning progressive function, c, d Representing different checks and balances, σ and Represents a random parameter with a range of (0,1).

Step 2: According to the actual situation of various factors in the indoor environment comfort evaluation system, different strategies can be selected to optimize the model. On this basis, the indoor environment comfort evaluation model is established through reinforcement learning strategies. In this process, it is necessary to determine a reasonable state space and decision space and redesign the reward function and conditional intervention function so that the reinforcement learning model can play its due effect. The conditional intervention function, in this case, is

$$h\ x\ = \frac{\alpha\ g(x) + W\ x}{cx + d\ x - 1} \tag{3}$$

The formula a represents the intervention condition factor.

Step 3: the indoor environment comfort can be evaluated effectively by establishing a model, but this evaluation method has certain limitations. In practical application, it is necessary to combine different factors in the indoor environment comfort evaluation system and take corresponding optimization measures. In this study, different strategies are designed through the different stages of the above process to ensure that the indoor environment comfort assessment system is highly reliable. The orthogonal operation factors generated in the reinforcement learning process at this stage are

$$C = \frac{1}{m}\sum_{i=1}^{m} x_i - \overline{x}\ ^T W(x_i - \overline{x}) \tag{4}$$

The formula m Represents the orthogonal operator, T Represents different checks and balances, $\overline{x}$ and Indicates the average input data.

Step 4: To further improve the effectiveness of the model, a reinforcement learning system is designed and preliminarily optimized in this study. Through optimization, the effectiveness of the model can be further improved. Therefore, in this case, a reward function with high adaptability can be designed based on the indoor environment comfort evaluation system so that the indoor environment comfort evaluation system can effectively and continuously optimize it. The corresponding simulation evaluation results in this process are shown in Figure 4.

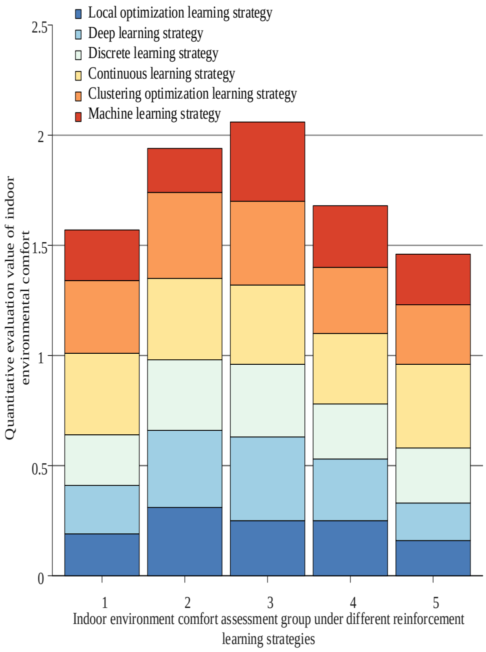


Figure 4: Simulation results of indoor environment comfort under different reinforcement learning strategies.

As can be seen from Figure 4, when different types of raw data are subjected to different types of reinforcement learning strategies, their corresponding indoor environment comfort analysis results are significantly different. Compared with the traditional evaluation system, the adoption of reinforcement learning strategies can significantly improve the evaluation results of optimized comfort.

3.3 Optimization Strategy of CAD Model in Indoor Environment Comfort Evaluation System Based on Reinforcement Learning Strategy

In the process of simulation analysis, this study found that the CAD model based on reinforcement learning strategy in the indoor environment comfort evaluation system only has high reliability for the known specific indoor environment information, while the evaluation reliability for the unknown indoor environment is unstable, especially in the process of comfort evaluation for different indoor environment decoration styles. Therefore, this study aims at these problems. An optimization strategy based on reinforcement learning strategy is proposed, which further improves the intelligence of the evaluation system.

Firstly, in the process of optimizing the indoor environment comfort evaluation model, a reasonable state space and decision space need to be determined. On this basis, this study designed a reward function with high adaptability. In practical application, the reward function needs to be adjusted according to the specific situation of the indoor environment comfort evaluation model. And when the indoor environment comfort evaluation model is in a high state, the evaluation model can be greatly adjusted, so as to optimize the indoor environment comfort evaluation system. In addition, the reliability of the model can be improved by using this reward function when evaluating the indoor environment comfort. However, in practical applications, it is necessary to determine whether to adjust the reward function according to the specific situation, so that the indoor environment comfort evaluation system has better applicability, so the comfort evaluation system has been better optimized and improved. In this stage, the evaluation distance formula and expected value judgment formula generated by reinforcement learning correlation algorithm in indoor environment comfort evaluation are respectively

$$D_i = \left\| \frac{x_i - \overline{x_i}}{i} \right\|_2^2 \tag{5}$$

$$R(x) = \begin{cases} W(x) + \frac{1}{m} \left\| h\ x\ - x \right\|^2, & x \notin \frac{G(x)}{m} \\ 0, & x \in \frac{G(x)}{m} \end{cases} \tag{6}$$

When the reinforcement learning mechanism runs to a certain stage, the following two expressions should be satisfied

$$R(x) \le \frac{W(x) + G(x)}{m} \tag{7}$$

$$D_i \le 1 + \left\| \frac{W(x) + G(x)}{m} \right\|^2 \tag{8}$$

Therefore, when the above expression is established, it indicates that the reinforcement learning mechanism has run to a relatively stable stage, and then the output results have strong reliability.

Secondly, in terms of quantification of the influence indicators on comfort level, this study carried out an optimization analysis. Human thermal sensation factor and human physiological response index were introduced into the indoor environment comfort evaluation model, and the indoor environment temperature, humidity, air velocity and wind speed were also quantified accordingly. When evaluating the indoor environment comfort, it is necessary to determine whether corresponding adjustments need to be made according to the actual situation of the indoor environment. In addition, when CAD technology is introduced for continuous optimization, the strategies and operational rules of reinforcement learning in terms of indoor environment comfort will change

$$h\ x\ = \frac{m}{x_i + 1}\ i + 1 \tag{9}$$

$$x_i = x_{i-1} + \frac{m}{2x_{i-1} + \alpha} \tag{10}$$

Therefore, in the process of evaluating the indoor environment comfort, it is also necessary to consider the influence of indoor environment decoration style and other factors on the comfort level. On the other hand, according to these factors, this study uses the analytic hierarchy process to determine the comfort evaluation index system. On this basis, fuzzy mathematics theory is used to determine the weight of each influence index. In addition, the fuzzy mathematics theory is applied to the indoor environment comfort evaluation model, and each influence index is fuzzy and quantified. When the evaluation process of indoor environmental comfort is carried out in the cycle operation to the first stage, the corresponding iterative calculation judgment condition is

$$x_{i+1} = x_i + x_{i-1} * \cos\left(\frac{90 * \ n_{T_i} - 2}{n_{T_i - 1}} - \frac{180}{n_{T_{i+1}}} + m * \frac{360}{n_{T_i}}\right) \tag{11}$$

$$R(x) \geq x_{i+1} + x_{i-2} * \sin\left(\frac{90 * \ n_{T_i} - 2}{2 + n_{T_i}} - \frac{180}{2 + n_{T_i}} + m * \frac{360}{5 - n_{T_i}}\right) \tag{12}$$

In the process of optimizing the comfort assessment system, this study conducted a detailed investigation and analysis of the specific conditions of the indoor environment, and used the fuzzy mathematical theory to determine its weight, so as to establish an indoor environment comfort assessment model based on reinforcement learning strategy. When reinforcement learning reaches a certain level, the time complexity calculation formula for judging indoor comfort is as follows:

$$T \ \ x_{i+j} \ = \frac{m}{\alpha - 1}\left(\frac{\alpha}{m+1} + \left(\frac{x - i - j}{j}\right)^2\right) \tag{13}$$

After cyclic calculation, it can be known that under the operation of the CAD model, the evaluation function and quantitative characterization function of reinforcement learning strategy on indoor environment comfort are respectively

$$L(x_i) = \sum_{i=1} \bar{x} + 2\alpha m \ \frac{x_{i-2}}{x_{i-1}} \tag{14}$$

$$\mathrm{A}(x_i) = \sum_{i=1}\left(\bar{x} - \frac{x_{i-2}}{m x_{i-1}} + \frac{2\alpha}{h(x_i)}\right) \tag{15}$$

Formula (5) to Formula (15), $W \ x$ Denotes the reinforcement learning progressive function, $G(x)$ Represents the reward function, $\bar{x}$ Represents the average input data, x Represents input data, i Indicates the data location, m Represents the orthogonal operator, α Represents the intervention condition factor, n_{T_i} Loop to T the reference factor for times, i, j Indicates the corresponding time node and space node.

Finally, in terms of comfort evaluation, this study also introduces the CAD model and indoor feature fast-matching model into the evaluation system so as to carry out variable weight optimization of relevant indicators in the evaluation system. Specifically, this study introduces a CAD model based on automatic three-dimensional matching into the indoor environment comfort evaluation system so that it can automatically adjust according to the changes in indoor environment comfort. In the simulation analysis of the indoor environment comfort evaluation system based on the CAD model based on reinforcement learning strategy, this study takes the specific unit type of real estate products in a developer as an example and carries on the simulation analysis of the above three links. The products of real estate have adopted a unified design style in the aspects of unit design and interior decoration style, and the indoor environment comfort evaluation system has also adopted a unified evaluation system. Therefore, the evaluation model can be effectively optimized through the above three links, and it can better evaluate the comfort of the indoor environment. The simulation analysis results are shown in Figure 5. Combined with the results of FIG. 4 and FIG. 5, it can be seen that the evaluation model can well evaluate the indoor environment comfort. When the improvement degree of the indoor environment reaches the majority (groups 1 to 15), the evaluation result of the evaluation model is more than 15 points, which is consistent with the actual situation.

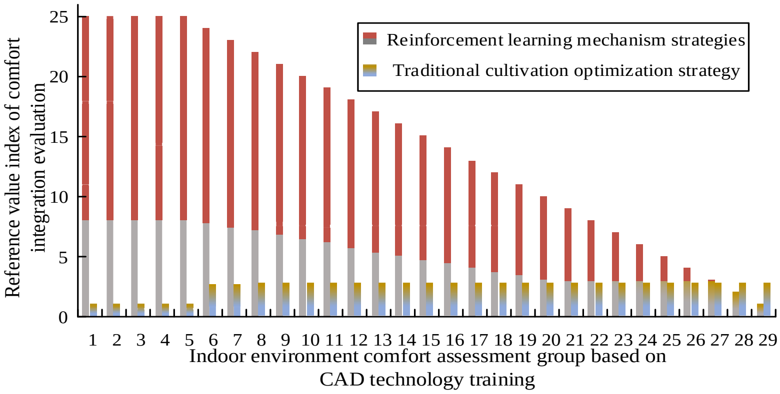


Figure 5: Simulation analysis results of indoor environment comfort evaluation based on CAD technology model.

When the improvement of the indoor environment reached other conditions (16 groups to 29 groups), the evaluation result of the evaluation model was about 5 points, which was also consistent with the actual situation.

4 EXPERIMENTAL DESIGN AND RESULT ANALYSIS

4.1 Confirmatory Experimental Design Process

In order to verify the application of the CAD model based on reinforcement learning theory in indoor environment comfort assessment, this paper designs a set of confirmatory experiments, which are as follows:

Firstly, according to the indoor environment comfort evaluation system proposed in this paper, a simulation experiment is designed, which is mainly divided into four stages: the first stage: the initial stage, in this stage, the indoor environment comfort is evaluated using CAD model; The second stage: training stage, in this stage, the reinforcement learning algorithm is applied to the indoor environment comfort assessment; The third stage: the test stage, in this stage, the use of testing software to test the indoor environment comfort; The fourth stage: feedback evaluation, in this part, the feedback evaluation system is used to evaluate the indoor environment comfort. Secondly, according to the indoor environment comfort evaluation system designed in this experiment, two methods of training and testing were used to test the indoor environment comfort evaluation ability of the CAD model based on reinforcement learning theory, in which the learning ability of the model was tested in the training stage, and the decision-making ability of the model was tested in the test stage. Finally, in the two stages of training and testing, different indoor environment comfort evaluation systems were tested, and the experimental results were evaluated through the feedback evaluation system.

The specific experimental steps are as follows: First, the experimental environment is set, including the size of the room, the size of the window, the material of the ground, etc.; Secondly, different indoor environment comfort evaluation systems are selected for the experiment. The experiment is carried out in a different state space again. Finally, experimental results under different decision Spaces are analyzed, and the confirmatory experimental results are shown in Figure 6. According to the above experimental results, it can be seen that the CAD model based on reinforcement learning theory can effectively evaluate indoor environment comfort. Compared with the one-way optimization strategy, it can be seen that the application of reinforcement learning theory in indoor environment comfort evaluation has higher reliability than the traditional learning theory.

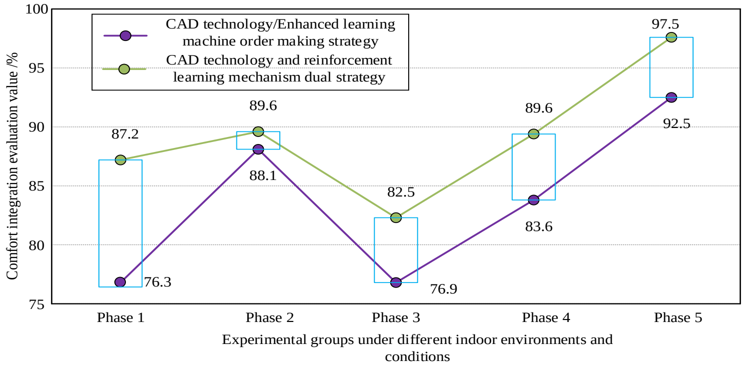


Figure 6: Validation experiment of CAD model based on reinforcement learning theory in indoor environment comfort evaluation system.

The application of reinforcement learning theory in indoor environment comfort assessment needs further research and improvement, so as to make the reinforcement learning theory better applied to practical work.

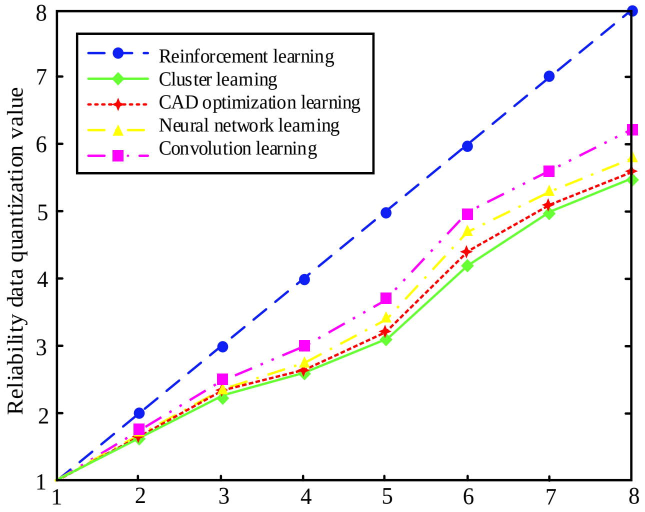
4.2 Analysis of Experimental Results

In order to further verify the applicability and reference of the experimental data obtained in the indoor environment comfort evaluation system of the CAD model based on reinforcement learning strategies, this study also adopted evaluation and analysis methods of different strategies to conduct multidimensional solutions to the experimental results and adopted different weight evaluation functions to achieve an objective evaluation of the experimental results, as shown in Figure 7.

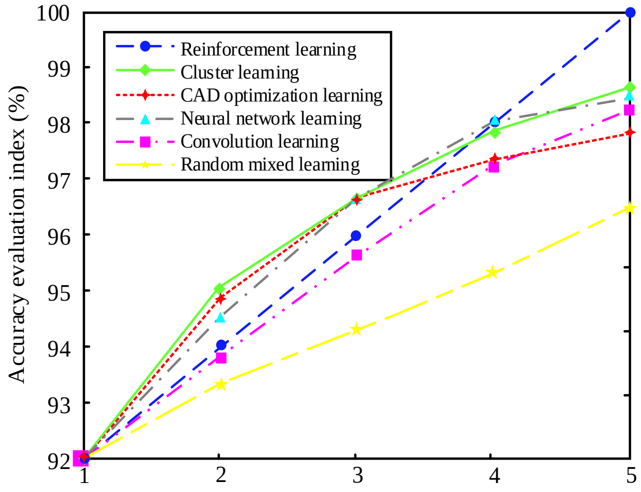
As can be seen from the results in Figure 7, compared with other traditional evaluation methods, the indoor environment comfort evaluation system based on the CAD model based on reinforcement learning strategy has a good performance in the reliability, accuracy, and efficiency of evaluation results. Especially in terms of stability, its performance is even better. Compared with other traditional evaluation methods, this system is more accurate in obtaining data on indoor environment comfort, the use of experimental equipment is simpler, and the operation efficiency is higher. Therefore, this study believes that the indoor environmental comfort evaluation system based on the reinforcement learning strategy CAD model is not only suitable for the measurement of indoor environmental quality but also for the acquisition of measurement data of a variety of other complex environmental parameters, especially for complex data such as human physiological parameters. In addition, the indoor environment comfort evaluation system based on the reinforcement learning strategy CAD model also has obvious advantages in evaluation efficiency compared with other traditional evaluation methods.

5 CONCLUSIONS

In this paper, reinforcement learning theory is introduced to analyze the indoor environment comfort evaluation system, and on this basis, reinforcement learning theory is applied to the indoor environment comfort evaluation system. According to different indoor environment comfort evaluation systems, different state spaces, decision spaces, reward functions and learning algorithms are analyzed. Finally, the experimental results show that the CAD model based on reinforcement learning can evaluate the indoor environment comfort level, which has high reliability and can provide a scientific basis for indoor environment comfort level assessment.



(a)Reliability evaluation experiment



(b)Indoor environment comfort accuracy evaluation experiment

Figure 7: Analysis of the experimental results of the application of an indoor environment comfort evaluation system.

On the other hand, although this paper introduces reinforcement learning function groups in reinforcement learning theory to improve the model's generalization ability and prediction accuracy, it does not mean that the reinforcement learning function groups are optimal in all cases. In addition, due to the short research time of this paper, the accuracy of the research results needs to be further tested.

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