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Intelligent Generation and Reinforcement Learning Strategy of Architectural Design CAD Models

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Abstract. The rapid development of information technology and artificial intelligence algorithms has had a profound impact on the real world, and new technologies have led many traditional industries to explore new development directions. In the field of architectural design, the continuous evolution of architectural design tools and iterative updates of design methods provide a good foundation for information-based architectural design. This article uses the intelligent generation function of CAD models combined with reinforcement learning strategies to study the reconstruction of architectural design drawings and the automatic layout of architectural design spaces. Firstly, various applications of CAD technology in construction engineering planning were analyzed, and the strategic application directions of reinforcement learning algorithms were explored. In the application environment of CAD technology, systematic analysis is carried out on modules such as assisting architectural designers in drawing, graphic editing, and data processing. The intelligent generation function of CAD models is used to complete automatic modelling and real-time rendering in three-dimensional space according to certain algorithms, optimizing architectural design drawings. Finally, in response to the issues of architectural design standards and spatial layout, reinforcement learning strategies are incorporated to treat individual buildings as intelligent agents. Through interactive accumulation with the scene, different building layouts and corresponding constraint problems are processed to achieve optimization of automatic layout in architectural design. The research results indicate that the use of CAD models in architectural design can only generate and reinforce learning strategies, which can optimize the drawing process of architectural drawings and improve the rationality of architectural spatial planning.

Keywords: Architectural Design; Cad Model; Intelligent Generation; Reinforcement Learning Strategy; Spatial Distribution
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1 INTRODUCTION

After a long historical development, people have gone from creating simple dwellings such as caves and shelters to constructing more complex structures such as stone, wood, and other buildings. Architectural design has accompanied the entire process of human social evolution. Buildings not only provide people with a place to live and work but also serve as the main carrier for expressing national beliefs and spirits. They influence people's production, living, communication, and folk culture. Correspondingly, there have been changes in architectural design tools. With the long development of society and productivity, architectural design tools have transformed from primitive to modern and information-based. The architectural design style is also becoming more intelligent and diversified. Architectural designers use paper and perspective drawing techniques to create layouts and structures for buildings. Craftsmen have also summarized the experience of building scale and the use of building materials from practice. With the rapid development of information and computer technology, people's lives have undergone new changes, which have also brought new opportunities to the field of architecture. In the 1970s and 1980s, two-dimensional mapping began to emerge [1]. These tools that can systematically draw complex images are widely used in industries such as construction, electrical, and machinery. With the continuous advancement of computer graphics and rendering technology, the emergence of CAD technology and CAD system models in three-dimensional environments enables designers to build more complex and high-tech modelling scenes. Virtual environments can also be created to simulate the lighting conditions inside and outside the building, allowing customers to roam in real-time in the virtual space and better appreciate the design details and spatial layout of the building. From this, it can be seen that computer-aided modelling tools such as CAD have brought new architectural spatial experiences and feelings to designers and users [2].

Part of the research utilizes intelligent CAD model generation technology to automatically design and optimize preliminary design schemes for low-rise buildings based on tropical climate characteristics. And allows dynamic adjustment of building elements such as window materials, exterior wall materials, and roof materials, as well as design details such as window-to-wall ratio and horizontal shading. Through intelligent algorithms such as genetic algorithms or deep learning models, multiple possible building design schemes can be explored in the early stages of design, and ten core features that affect cooling load can be automatically extracted [3]. Combine the optimized machine learning (especially histogram gradient boosting and stacking models) cooling load prediction model with an intelligent CAD model generation system to form a closed-loop feedback mechanism. Reinforcement learning agents can explore different design strategies in simulated environments, and through continuous trial and error and learning, find the best design solution that can meet functional requirements and effectively reduce cooling load under specific climate conditions. The prediction model predicts the cooling load based on the design parameters of the current CAD model, while the intelligent generation system adjusts the design parameters according to the prediction results to further reduce the predicted cooling load [4]. This process not only improves design efficiency but also promotes the birth of innovative design concepts. Ultimately, by comprehensively evaluating the cooling load prediction results, building costs, energy efficiency, environmental impact, and other dimensions under different design schemes, comprehensive decision support is provided for architects and decision-makers. Intelligent systems can generate detailed design reports, including cooling load forecasting diagrams, cost-benefit analyses, environmental impact assessments, etc., to help users make more scientific and reasonable building design decisions [5]. These CAD models integrate key structural parameters such as building area, aspect ratio, and ceiling height. After the CAD model is generated, a reinforcement learning strategy is introduced to further optimize the building design, to directly adjust for the goal of minimizing cooling load. This linkage mechanism can evaluate the impact of design changes in real-time and iterate quickly to find the optimal design solution [6].

In the past few decades, with the rapid development of technology, Computational Design (CD) has not only occupied a pivotal position among architects and designers but also profoundly reshaped the practice and innovation path of architectural design. Based on an in-depth exploration of Computational Design (CD), some scholars have combined "Intelligent Generation and Reinforcement Learning Strategies for Architectural Design CAD Models" [7]. However, with it comes the diversity and inconsistency of terminology usage, which poses challenges for cross-disciplinary communication and knowledge sharing. This proposes a clearer and more robust classification system for key CD terms such as parameter design, generative design, and algorithm design. Under the CD framework, intelligent generation of architectural design CAD models has become an important branch. This process relies not only on precise mathematical models and algorithms [8]. These methods not only improve design efficiency but also greatly expand the potential boundaries of design. Intelligent generation systems can handle complex building geometry, material properties, and environmental factors, generate diverse design solutions, and provide real-time feedback on design effects, greatly improving design efficiency and the breadth of creativity. In intelligent CAD model generation, parameter design is used to establish a relationship network of design variables. By adjusting these parameters, the system can automatically generate a series of variant schemes for designers to choose from or further optimize [9]. It also incorporates artificial intelligence and machine learning technologies, enabling CAD models to be automatically or semi-automatically generated and optimized based on preset rules, design constraints, and user preferences. Parameter design, as the foundation of CD, makes the design process flexible and controllable by defining a series of variable parameters such as building dimensions, material properties, spatial layout, etc. The core of parameter design lies in its ability to quantify design decisions, making the design process more scientific and predictable [10].

The transformation of architectural design tools has greatly improved the updating of architectural design styles and brought more reliable guarantees for building quality. The transition from manual drawing to computer-aided drawing reflects the increasingly intelligent nature of architectural design. In addition, the architectural design process can essentially be seen as a process that includes multiple constraints and is also a solution process for complex systems [11]. Simply put, the building system includes the needs of the masses, the surrounding environment, and daily lighting parameters. It can be seen that considering various factors, such as site and address parameters in architectural design, will bring certain tests to the architectural design model. If these abstract conditions are viewed as the process of solving a series of mathematical problems, then deep learning algorithms are needed as the core technical support. The reinforcement learning strategy in deep learning algorithms has broad application prospects in the field of intelligent data computing. Reinforcement learning strategies are also a fusion of various functions, such as environmental interaction and autonomous learning. Utilizing advanced intelligent algorithms to calculate the optimal strategy for spatial layout in architectural design, thereby providing designers with more reliable references in the selection of building environments [12]. Therefore, computer-aided CAD models and reinforcement learning strategies have their unique characteristics and irreplaceable functions in architectural design. In our research, we also focus on using two techniques to explore the drawing of architectural design graphics and spatial layout optimization.

2 THE DEVELOPMENT STATUS

Architectural space not only provides a place for human activities, but also represents people's expression of life, culture, spirit, and faith. Therefore, architecture is a field that combines disciplines with art, and architects need to possess both the aesthetic characteristics of artists and the rational thinking of engineers. The fusion of two disciplines has developed into a significant design inspiration, and this creative work involves a large amount of data and information. At the same time, with the help of information technology and modern technology, CAD models have brought new vitality to the field of architectural design. CAD technology, also known as computer-aided technology, is a means of completing architectural design work by relying on computer systems and corresponding software to assist manual labour. It originated in the 1970s and was widely used in the fields of management and engineering budgeting by quickly obtaining results through computer programming. Over time, CAD technology has become increasingly mature, and various enterprises have also launched various CAD derivative software.

The work of urban designers relies on highly customized design elements and symbols, which form their unique design language. Although artificial intelligence can effectively generate a large number of design solutions, the essence of humanized design lies in a profound understanding and integration of spatial, cultural, social, and environmental factors. Intelligent CAD models should be able to simulate and evaluate the impact of different design schemes on on-site creation during the generation process. Through data analysis and visualization methods, Simtinică et al. [13] have better understood and optimized the design scheme. Therefore, the generation of intelligent CAD models should pay more attention to collaboration with designers, continuously learning and optimizing their algorithms from designers' decisions through reinforcement learning strategies, to generate works that are more in line with the concept of humanized design. Venue creation is an indispensable part of urban design, which is related to the creation of spatial atmosphere, the inheritance of historical culture, and the establishment of community identity. Artificial intelligence technology can provide accurate information on traffic flow, environmental impact, and other aspects for urban designers through big data analysis and simulation prediction, effectively avoiding potential problems in the design phase and improving the overall livability of the city. The construction of livable cities requires comprehensive consideration of multiple dimensions such as transportation, environment, and quality of life. In the complex world of design, there are many repetitive tasks. The intelligent CAD model generation software should support highly customized toolboxes and seamlessly integrate with AI technology, enabling Stojanovski et al. [14] to easily access AI-assisted functions while maintaining comprehensive control over the design process. Artificial intelligence technology can automate these behavioural patterns, freeing up more time and energy for designers to focus on creativity and decision-making. However, this process requires ensuring that the intervention of artificial intelligence does not weaken the creativity and personality expression of designers.

Intelligent CAD models are not limited to digital representations of building appearance and structure but can also integrate energy management elements such as thermal performance and renewable energy potential. Reinforcement learning strategies can guide parameter adjustments during the CAD model generation process, ensuring that the design scheme achieves optimal energy efficiency while meeting functional requirements. This adaptive capability enables the SBEM system to respond flexibly to various changes, ensuring efficient and stable energy use. Through DRL technology, CAD models can predict and optimize the energy consumption performance of buildings during the design phase, achieving "design energy efficiency." Faced with uncertain factors such as renewable energy generation, outdoor temperature, and the number of residents, DRL can dynamically adjust building energy management strategies through continuous learning and interaction with the environment. The combination of intelligent CAD models and DRL can further refine the simulation and verification of these constraints, ensuring the feasibility of the design scheme. DRL exhibits unique advantages in handling complex constraints. Meanwhile, with the accumulation of learning data and optimization of models, the universality of the DRL algorithm will gradually improve, providing effective energy management solutions for more types of buildings. Willis et al. [15] constructed a reward function that includes spatial and temporal coupling constraints, allowing the DRL algorithm to learn how to optimize building energy consumption while satisfying these constraints. For the vast solution space in SBEM problems, DRL can find near-optimal solutions within a limited time through its efficient exploration and utilization mechanism. Intelligent CAD models provide rich design space, enabling DRL algorithms to search and optimize on a larger scale. Specific building environments often limit traditional building energy management methods. By combining DRL technology with intelligent CAD models, customized energy management strategies can be developed based on the characteristics and needs of different buildings.

In the early stages of CAD technology development, it was limited by basic software and hardware, with relatively single functions and no graphic interaction capabilities. Many tasks in architectural design are still completed manually. However, in recent years, the emergence of second-generation CAD systems has led to a diversified development trend of CAD software, which can meet the needs of the vast majority of building structural design. Xu et al. [16] analyzed the fact that CAD technology developed relatively early abroad. Designers use CAD simulation software to construct energy consumption processes in the model and import indoor and outdoor design parameters such as average temperature, zone type, and building structure into the model, simplifying the entire process of building design. At the same time, the software can also provide physical descriptions of building structural performance and characteristics. In addition, countries such as the UK also use CAD technology as a functional reference for optimizing building energy efficiency. They designed a detailed energy-saving plan and ultimately set the bidirectional building energy efficiency optimization mode as the expected design goal. The energy-saving design of this building ensures that the living environment meets the standards of modern green development. As an intelligent strategy computing model that combines deep learning and neural networks, reinforcement learning algorithms play an important role in various fields, such as robot control, automation scheduling, quality control, and building design. It can help the industry improve production efficiency while ensuring product quality and service levels. In terms of automation control, reinforcement learning algorithms can complete mechanical path planning, attitude control, and action selection and achieve efficient and flexible structural design based on the motion laws of intelligent agents and surrounding environmental information. This intelligent and automated decision-making plays an important role in the field of architectural design. Yu et al. [17] began to focus on the application effect of reinforcement learning strategies in architectural design space layout and proposed an automatic space allocation model based on reinforcement learning algorithms. Using model calculation and decision control to achieve quality optimization in architectural design. On this basis, this article also conducted optimization research on the architectural design process based on the intelligent generation effect of CAD models and the automatic layout planning of reinforcement learning strategies.

3 RESEARCH ON INTELLIGENT GENERATION OF ARCHITECTURAL DESIGN STRUCTURES

3.1 Research on Intelligent Generation of 3D Reconstruction of Architectural Design Drawings Based on CAD Models

With the development of digital and smart cities, people's demands for architectural design are becoming increasingly diverse. As an important component of cities, the three-dimensional reconstruction of architectural drawings is also a key focus of designers' work. The generation of architectural design drawings requires combining two-dimensional image information and spatial information, which is also a key content for the three-dimensional expression of building objects. As the main construction basis, the information in building drawings must be detailed and easily accessible. At present, many computer-aided tools are used in architectural design, among which CAD technology, as the most widely used tool, has also demonstrated its unique advantages. The high difficulty of interpreting traditional two-dimensional drawings and the lack of intuitive three-dimensional information have made intelligent generation of CAD models the main architectural design method chosen by designers. The extraction of two-dimensional information from architectural drawings can construct high-precision three-dimensional building models. Buildings can be classified into three types of building requirements: civil, industrial, and agricultural, based on their functions and uses. We use data to investigate and statistically analyze different types of buildings in these three directions and draw the following table:

Building direction	*Building type*	
Civil architecture category	Residential buildings	Residential community

		Dormitory
		apartment building
	Public buildings	CULTURE ARCHITECTURE
		Medical buildings
		Commercial buildings
		sports building
Industrial architecture category	workshop	
	warehouse	
	boiler room	
	Chimney water tower	
Agricultural Architecture category	Plant architecture	greenhouse
		agricultural machinery station
	Livestock buildings	cowshed
		chicken farm

Table 1: Different types of buildings in three different directions.

According to Table 1, the categories of civil buildings include people's daily lives, such as residential areas, dormitory buildings, apartments, etc. Public buildings include cultural buildings, medical buildings, commercial buildings, sports buildings, etc. In the category of industrial buildings, there are various types of building types required for production, represented by factory buildings, including factories, warehouses, boiler rooms, chimneys, water towers, and other structures. In the category of agricultural buildings, they can be divided into plant buildings such as greenhouses and agricultural machinery stations, as well as breeding buildings such as cattle sheds and chicken farms. The types of buildings targeted by architectural design are generally complex. This article uses CAD models to complete the information processing of architectural design and uses CAD models as the carrier of architectural data to calculate and adjust various detailed parameters in software. Through investigation of relevant information, we have learned that the design and reconstruction of architectural drawings can be divided into three types based on the degree of automation: manual, semi-automatic, and fully automatic. In traditional manual reconstruction design and drawing, technicians first need to interpret the semantic information contained in the floor plan, and then complete the spatial construction through professional modeling software. Both information extraction and modelling processes require manual intervention. The semi-automatic 3D reconstruction usually takes the form of technicians importing drawings into semi-automatic software according to certain rules, inputting relevant parameters, and manually constructing building space models. Compared to manual and semi-automatic reconstruction methods, the generation process of automated 3D architectural design drawings does not require human involvement. Automated software can intelligently complete map recognition and modelling, quickly generate 3D models through recognition algorithms and modelling scripts, and comprehensively consider the data acquisition process. Among them, CAD intelligent model generation is the most representative automatic tool.

The application frequency of semi-automatic architectural design and reconstruction has also shown a decreasing trend. The application frequency of CAD intelligent generation models has significantly increased and shown a good development trend. To achieve a refined design for complex architectural drawings, we need to analyze the main components and parts of the building. Based on graphic semantics and geometric topology relationships, detailed design details are added to the CAD intelligent generation model, thereby improving the design quality after 3D modelling and restoring more content of the building. According to the research direction, the technical roadmap of this article is determined as shown in Figure 1:

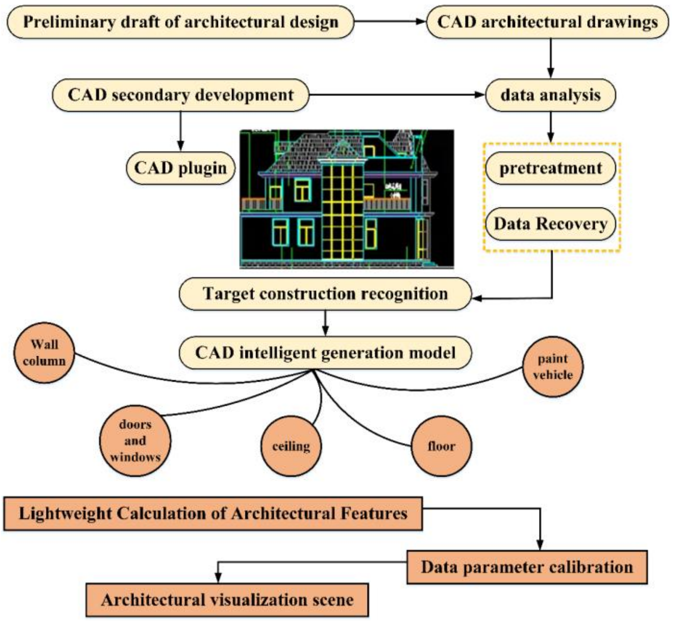

Figure 1: This article presents a technical roadmap.

As shown in Figure 1, according to the architectural design requirements, the accumulated architectural drawings are obtained, and the 3D data analysis is completed using the secondary development tool of CAD models. After data preprocessing and data restoration, target construction recognition is carried out, and the construction of a 3D reconstruction system is completed in the CAD intelligent generation model. Input the recognition results into the lightweight calculation process of building characteristics, complete the calibration of data parameters, and finally generate a visual scene using the model. The intelligent generation of architectural design drawings using CAD models allows for the adjustment of parameters at any time and the completion of reasonable structural combinations based on architectural design requirements.

3.2 Research on Automatic Optimization of Architectural Design Space Layout Based on Reinforcement Learning Strategy

Due to the acceleration of urbanization and the increasing scarcity of land resources, architectural design is an important component of developing modern cities. Many areas have irregular and complex environments in terms of land parcels and contours. The architectural layout space needs to meet multiple building code requirements such as sunlight, fire protection, and disaster prevention. The effective sunshine duration and cumulative sunshine duration need to be calculated for residential buildings. The sunshine spacing used in multi-story residential buildings can directly affect the lighting conditions inside the building. In addition, the height distribution and spatial layout of high-rise buildings and surrounding buildings interact with each other, forming a non-linear and complex relationship. In traditional architectural layout design, architects can only complete analysis based on rough indicators, quantify and adjust design schemes according to specific calculation standards, and make them meet the corresponding environmental performance requirements. This practical operation can only be completed manually with professional skills. The complexity of the elements involved in architectural design is high, and the continuous trial and error process often requires a significant amount of manpower and time costs. Therefore, utilizing the accurate and objective advantages of information technology to assist in architectural layout design has become a new approach. However, current software related to architectural design can only provide static data analysis tasks and cannot serve as direct guidance. The different values of building location, floor height, space, and other information also generate a significant amount of interference in data optimization iterations, resulting in an exponential increase in solution time.

Therefore, to optimize and adjust the architectural design space and surrounding environment, we use reinforcement learning strategies and multiple constraint conditions in complex situations to efficiently and accurately calculate a reasonable design model. Reinforcement learning strategies can achieve machine learning training through interaction between agents and the environment, demonstrating a high degree of automation and intelligence in design. Optimize design drawings with the help of surrounding information while meeting the basic requirements of residential design and land use needs and restricting multiple elements within the same algorithm framework to ensure continuous transmission and modification of data. As an intelligent agent, the building body directly interacts with the environment and incorporates the received scene feedback information into the reinforcement learning strategy calculation to ensure that the output solution meets the actual building requirements in terms of accuracy and quality. We will present the framework diagram for the automatic optimization of multi-scenario building spatial layout provided by reinforcement learning strategies as follows.

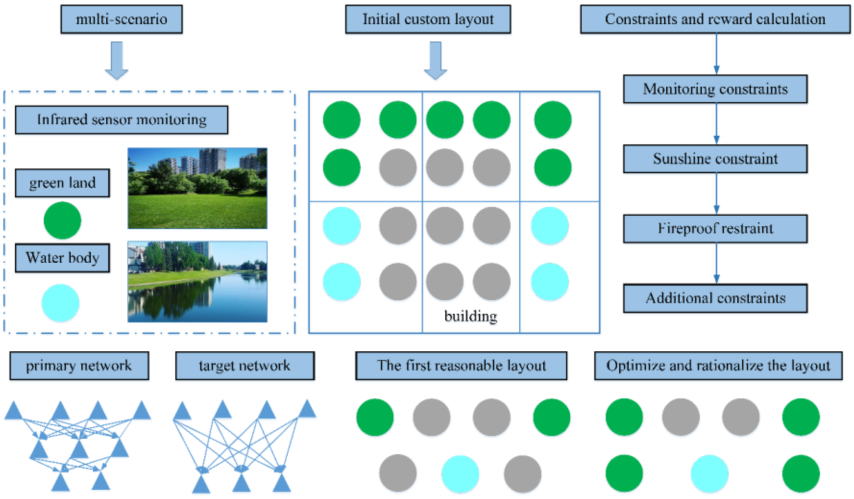

Figure 2: Framework diagram for automatic optimization of multi-scene building spatial layout.

From Figure 2, it can be seen that infrared sensors are used to monitor the surrounding environment in multiple scenarios, and the green spaces, water bodies, and other content required for architectural design are added to the initial custom layout. Using reinforcement learning strategies to calculate spatial requirements such as sunlight and disaster prevention in architectural design based on constraints and calculated rewards. Add the calculation results to the main network to complete the drawing of the model output scheme. In the model output scheme module, compare the initialized layout with the optimized layout. In reinforcement learning strategy computation, the boundary centre of the architectural design is taken as the origin. Considering the parameter activity range of intelligent agents in the scene, the spatial formula is defined as:

$$a = [Noop, a_x, a_{x+}, a_y, a_{y+}] \tag{1}$$

In the formula, a represents the original coordinates without any operation. The default formula for the environmental cycle is:

$$v_x' = v_x + (a_0 - a) * T \tag{2}$$

$$v_y' = v_u + (a_1 - a_0) * T \tag{3}$$

The updated coordinate position of the intelligent agent is:

$$x' = x + v_x * T \tag{4}$$

$$y' = y + v_y * T \tag{5}$$

Scene is a key factor in intelligent agent interaction, therefore, when observing spatial states and executing action strategies, it is necessary to define calculation formulas reasonably:

$$s = [v_x, u_y, x - x_i, y - y_i] \tag{6}$$

$$X = \ x_1, \ldots, x_N \tag{7}$$

The formula s represents the distribution position information of the current intelligent agent on the coordinate axis. Due to the multi-scenario constraints considered in this article, including sunlight, water bodies, green spaces, building spacing, and other factors. We need to extract and calculate multiple constraints in architectural layout design:

$$C = \begin{cases} 0, N_1 = 0 \\ -10000, N_1 \neq 0 \end{cases} \tag{8}$$

$$C_{fie} = \begin{cases} 0, A_{fie} = 0 \\ -A, a_1 \neq 0 \end{cases} \tag{9}$$

Due to the complexity of seemingly different single objectives with multiple constraints, a reasonable building layout needs to simultaneously satisfy multiple objectives. Therefore, in optimization calculations, it is necessary to overlay building layout schemes. The definition formula is as follows:

$$x = x_i + \cos(3\pi / 2 - A, \pi / 180) L \tag{10}$$

$$L_0 = \sum \ l_i, i = 1, \ldots 3 * N \tag{11}$$

Optimize formula structure using reinforcement strategy:

$$C_{all} = C_{sun} + C_{fie} + C_{la} + Cc_{add} \tag{12}$$

Initialize the layout state, select relevant parameters based on the current computing network, remove interference noise, and obtain the reward function:

$$\varepsilon a_t = \mu(s \mid \theta^u) + N_t \tag{13}$$

$$s = (s_t, a_t, r_t, s_{t+1}) \tag{14}$$

The formula a_t represents the main body of the function after noise removal. Randomly collect multiple pieces of data from the experience pool as the training source for the network, and calculate the final building space valuation as follows:

$$P = \frac{1}{N} \sum_u^i (y - Q(s, a \mid \theta^Q))^2 \tag{15}$$

Based on the above formula output, the final architectural design spatial layout structure under the reinforcement learning strategy is obtained, and the automatic update function of the model itself is utilized to complete layout adjustments that adapt to different surrounding environments.

4 ANALYSIS OF RESEARCH RESULTS ON INTELLIGENT GENERATION OF ARCHITECTURAL DESIGN STRUCTURES BASED ON CAD MODELS AND REINFORCEMENT LEARNING STRATEGIES

4.1 Analysis of Research Results on Intelligent Generation of 3D Reconstruction of Architectural Design Drawings Based on CAD Models

The overall floor plan of a building can project the entire building area from top to bottom onto a horizontal plane, completing an orthographic projection display. In traditional architectural design drawings, many elements such as the terrain of the building site, buildings, structures, roads, and green land can only be reflected on a two-dimensional plane. The CAD model used in this article can intelligently generate 3D drawings of architectural design drawings. Comparing the detailed differences between traditional 2D drawings and intelligently generated 3D drawings, as shown in Figure 3.

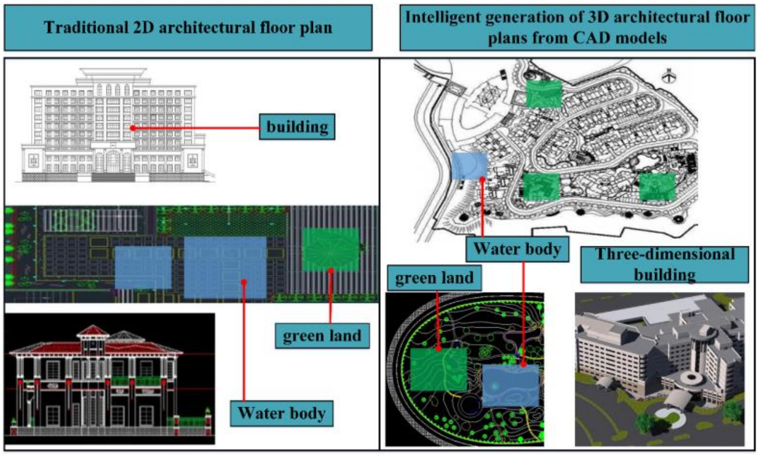

Figure 3: Detail differences between traditional 2D drawings and intelligently generated 3D drawings.

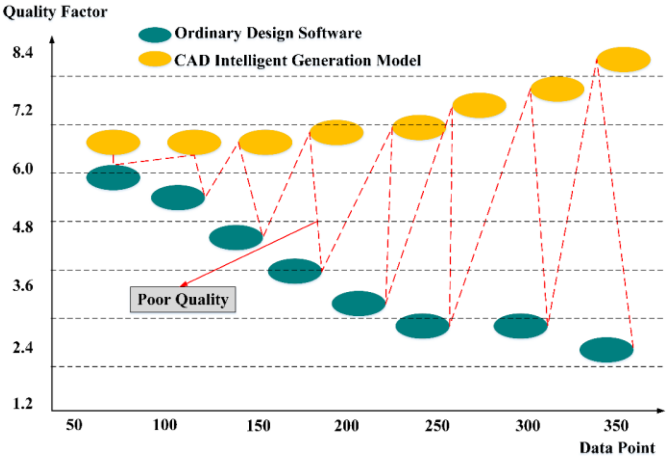

Figure 4: The effect changes of in CAD models and ordinary design software on the quality of drawing generation.

From Figure 3, it can be seen that although traditional two-dimensional architectural floor plans mark various distributions such as greenery, water bodies, and buildings, the content is relatively complex, which is not conducive to the analysis and actual construction process of architects. This article uses CAD models to intelligently generate 3D architectural design drawings, incorporating the surrounding environment of the building into the three-dimensional environment, allowing for a visual representation of the actual building scene. At the same time, there are many data factors involved in the generation of architectural design drawings, and ordinary design software is prone to quality defects in the final generation when processing large amounts of data. We compare the changes in the quality of drawing generation between CAD models and ordinary design software.

From Figure 4, it can be seen that ordinary design software faces the influence of a large amount of dynamic data, resulting in poor quality of the final drawings generated. The quality coefficient of architectural design drawings generated intelligently using CAD models is relatively high.

4.2 Analysis of Research Results on Automatic Optimization of Architectural Design Spatial Layout Based on Reinforcement Learning Strategy

As the number of buildings increases, architectural design and spatial layout play an important role in dividing the entire area. In architectural design, spatial planning and spatial distribution solving are complex computational problems. Traditional design generation cannot guarantee that the design results meet the needs of the surrounding environment. Therefore, in this study, reinforcement learning strategies are used to address the complex issues of regional buildings and surrounding environments and automatic spatial layout optimization is proposed. Using the boundary of a certain area as the centre origin, the contour is annotated using key point coordinates. After dividing the overall area of architectural design, key point data is added to the reinforcement learning strategy model. Due to factors that affect the layout of buildings, including lighting, greenery distribution, water distribution, etc. In exploring the effectiveness of the algorithm, we compared the average sunshine duration before and after using reinforcement learning strategies, as shown in Figure 5.

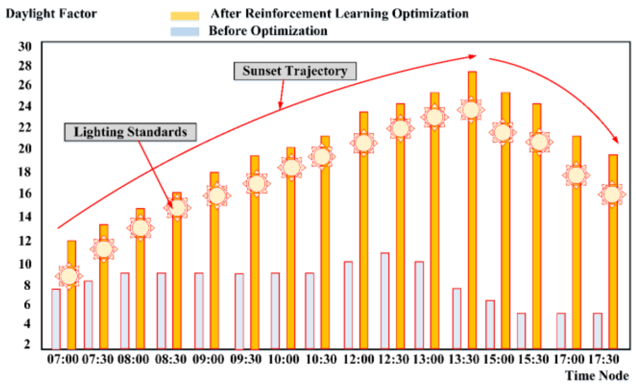

Figure 5: Average sunshine duration before and after using reinforcement learning strategies.

From Figure 5, it can be seen that the horizontal axis in the comparison chart represents the time nodes of each day. Before using the reinforcement learning strategy to optimize the spatial layout, the overall coefficient of average sunshine duration was relatively short. After optimizing the spatial layout using reinforcement learning strategies, the average sunshine duration conforms to the time nodes of the day and the changes in sunlight, and the sunshine duration is also guaranteed to be above a certain coefficient. To further validate the effectiveness of reinforcement learning strategies in the automatic optimization of building spatial layout, we also compared and detected the density values of water bodies and green spaces around the building design.

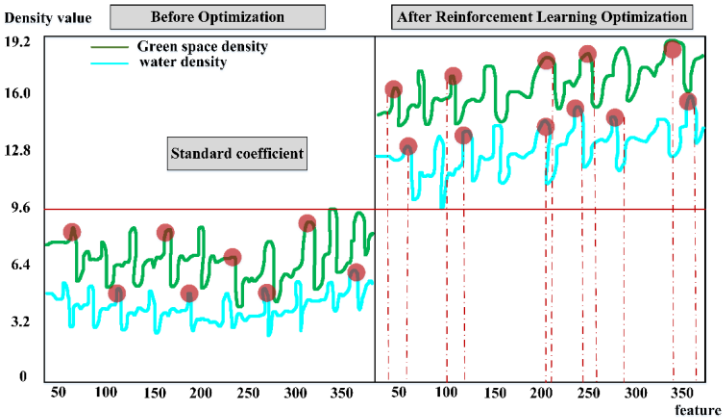

Figure 6: Changes in density values of water bodies and green spaces before and after using reinforcement learning strategies.

From Figure 6, it can be seen that before the reinforcement learning strategy optimization, the density values of surrounding water bodies and green spaces were relatively low, far below the standard requirements. This indicates that the surrounding environment of the unoptimized architectural design space does not meet the standard construction requirements. After adopting reinforcement learning strategies for optimization, the density values of surrounding water bodies and green spaces showed a significant upward trend, with higher density values and a better surrounding environment. In the subsequent initial layout, reasonable layout, and optimized layout information, it can also be found that the architectural design space and spacing between buildings automatically updated using reinforcement learning strategies are reasonable, and the lighting meets the normal residential needs. In addition, reinforcement learning algorithms can quickly converge to stable values based on differences in data environments in different spatial requirements, and assist in building planning.

5 CONCLUSIONS

The field of architectural design has always been an important component of developing modern cities. Today, with the continuous improvement of information technology and intelligent technology, architectural design tools have also undergone new changes. This article studies the intelligent generation function and reinforcement learning strategy of CAD models for architectural design drawing and automatic optimization of spatial layout. Firstly, the application status and research background of CAD technology and reinforcement learning strategies were introduced. Analyzed the issues of drawing generation and spatial layout in current architectural design. Based on building foundation construction, CAD models are used to identify the internal structure of the entire building and fast automatic modelling methods are adopted to establish a three-dimensional model and complete real-time rendering of the building model. By utilizing the similarity between building components, optimize CAD models to achieve the goal of lightweight building design drawings. Finally, with the help of reinforcement learning strategies, the optimization of the automatic spatial layout of buildings is completed. Perform numerical calculations and model iterative training on various specifications related to building layout, including lighting requirements, greening requirements, water requirements, spacing requirements, etc. Complete the spatial design of actual architectural scenes within a unified framework of multiple constraints and optimization objectives. The research results indicate that the intelligent generation of CAD models and reinforcement learning strategies can simplify architectural design drawings, optimize architectural spatial layout, and make designs more in line with actual scene requirements.

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