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Computer-Aided Design AND APPLICATIONS

Landscape Planning Aided by Reinforcement Learning Decision System in Environmental Design

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Abstract. As the core component of environmental design, landscape planning aims to create beautiful and practical public space through scientific and reasonable layout and design. In this study, a landscape planning decision-making model based on computer-aided design (CAD) and reinforcement learning (RL) is constructed, which makes full use of the accurate drawing and modelling capabilities of CAD software and the intelligent decision-making capabilities of the RL algorithm. Through comparative experiments, the proposed model is compared with the particle swarm optimization (PSO) algorithm on three different types of landscapes, and its performance in feature dimension reduction, terrain, and landscape overlay accuracy, and operation efficiency is assessed. The findings indicate that the proposed model exhibits a notably reduced dimension reduction time compared to the PSO algorithm while also enhancing the feature retention rate. It demonstrates the highest accuracy in terrain and landscape superposition, aligning closely with real-world conditions. Furthermore, the model performs well in terms of operational efficiency. Looking ahead, the system promises to assume a pivotal role in urban environmental design, offering robust assistance in crafting an improved and sustainable urban landscape.

Keywords: Environmental Design; CAD; Landscape Planning; Reinforcement Learning
DOI: https://doi.org/10.14733/cadaps.2025.S7.175-187

1 INTRODUCTION

At present, the updating mode of landscape space in China has entered a new stage of pursuing development quality and connotation through micro updating and quality improvement rather than scale-based incremental development [1]. Based on the above research background, some scholars choose interactive landscape installations as the research object, artistic experience theory as the research entry point, and based on the current situation and needs of urban renewal in China, explore the breakthrough point of the innovative design of interactive landscape installations. Relying solely on macro-level urban planning can easily overlook the specific design needs of urban public spaces, making it difficult to meet people's aspirations for a better city. Empower urban spaces with more humanized and experiential design content from the perspective of urban experiences. In this era, facing a series of urban design issues such as homogenization of urban design, formalization of urban landscape, and commercialization of public spaces [2]. Starting from the national urban renewal policy and the new requirements of the people for urban spatial quality, it is not difficult to find that China's urban renewal stage has gradually transitioned from an expansive urban management model of major repairs and constructions to a precise urban repair model. Then, the cognitive methods of art experience theory were analyzed and combined with the design process of interactive landscape installations, summarizing the application framework of art experience theory in interactive landscape installation design. Therefore, both the theoretical research on urban development and the actual situation of urban construction and renewal in China indicate that designers need to stand from the perspective of the public in the current new stage of urban renewal. This provides a new design method for interactive landscape installations in the context of urban renewal in China and stimulates innovative vitality [3].

With the advent of the digital age, technology has been integrated into every aspect of our lives, deeply changing the way we live, work, and interact with our surroundings. This shows people's love and dependence on technology. Some scholars use interdisciplinary research methods to demonstrate the directionality and feasibility of interactive landscape design in urban commercial spaces under the digital concept. With people's pursuit of spiritual satisfaction and filling in on top of improving their material foundation in today's society, digital concepts have influenced people's cognitive and value level changes towards new things and scenes in the process of urban renewal and development. In the current stage of smart city development, the design and expression of digital landscapes in urban commercial spaces have become increasingly important. Combining the interactive design forms of digital landscapes in urban commercial spaces summarizes the digital concepts, characteristics, and iterative effects that digital landscapes bring to urban commercial spaces [4]. The relationship between urban commercial space and the digital landscape is studied from the perspective of interaction and user experience needs, investigating the impact of the digital landscape in commercial space on audience psychology and behavioural hierarchy. The integration and complementarity of "landscape design" and "interactive design" is the perfect fusion of art and technology in commercial spaces. It is precisely because of this passion and need that people have higher expectations for digital technology. Faced with challenges such as global warming and water scarcity, landscape planning needs to pay more attention to long-term sustainability. By setting the objective function of maximizing environmental benefits, the system can gradually adjust the design scheme and ultimately generate a landscape planning scheme that is both beautiful and environmentally friendly. This human-machine collaborative working mode can fully utilize human creativity and machine computing power, jointly promoting innovative development in the fields of landscape planning and environmental design. Combining human-centered Web 4.0 and AI technology, reinforcement learning systems can not only automatically optimize design solutions but also interact with designers in real time, provide design suggestions, and receive feedback from designers [5].

Given that there is currently no universally applicable landscape design implementation model in China, some scholars not only recognize the importance of urban environmental design in promoting sustainable development but also strive to fill this gap by introducing innovative technologies to promote progress in this field. Through reinforcement learning decision systems, it is possible to simulate the long-term impact of different policies and planning strategies on urban development and evaluate their contributions to residents' quality of life, resource utilization efficiency, and ecological environment protection [6]. Digital media art is not only a simple field of digital science and technology but also a comprehensive professional field that integrates humanities, social sciences, and natural sciences. The main purpose of the research is to use digital media technology as an innovative technological tool and apply modern artistic aesthetic ideas in urban landscape design in the new era, revolutionizing the basic concepts and methods of urban landscape design. Its art forms cover many fields, from flat to three-dimensional, from simple to diverse, completely changing the teaching methods of traditional architectural art and design majors. As a technological means that combines emerging science and art, digital media art is gradually being introduced into the field of urban landscape design. The construction and design of modern urban landscapes are mainly guided by technology, urban planning principles, and modern artistic thinking theories, and technology is a decisive force. Greatly transformed the artistic expression and creative concepts of urban landscape engineering design, enhancing the interaction between urban landscape and the public. Some scholars will use evaluative and explanatory methods to explain how innovative forms of digital media art can lead to urban landscape engineering design. Therefore, the deepening of digital media art into the field of urban landscape design has become an irreversible trend in the digital century. Let innovative urban landscape engineering design and the rapid development of urbanization go hand in hand. Enhance the new urban appearance and living space experience through intelligent, digital, and humanized interactive experiences [7]. By comparing the planning effectiveness of traditional planning methods with CAD-assisted reinforcement learning decision systems, we found that the latter exhibits significant advantages in improving planning efficiency, enhancing environmental adaptability, and promoting resident satisfaction. This not only helps to formulate more scientific and reasonable municipal infrastructure management policies but also provides strong support for building a green, low-carbon, and livable urban environment. In order to verify the effectiveness and adaptability of the system, a comparative analysis was conducted between the development vision and existing research methods. This indicates that cities have a certain technological foundation and market demand in introducing intelligent services, architecture, and landscape planning, laying a solid foundation for implementing more advanced urban environmental design technologies [8].

Combining CAD with an RL decision-making system can give full play to the advantages of CAD in terms of design efficiency and accuracy and realize automatic optimization of design schemes with the help of RL's intelligent decision-making ability. This intelligent design mode is also helpful in promoting the digital transformation of the environmental design industry, promoting the sharing and collaboration of design resources, and providing strong support for building a greener, smarter, and more sustainable urban environment [9]. Through theoretical analysis and empirical research, it is expected to reveal the design process, key technology, and application effect in practical projects and provide new ideas for designers and researchers in the field of environmental design. Furthermore, this study will also pay attention to the potential and challenges of this integration model in promoting design innovation, improving design efficiency, and optimizing the decision-making process to provide reference and practice for future research.

(1) A decision-making model of landscape planning based on CAD and RL is established in this study, which can automatically explore and find the optimal design strategy.

(2) Compared with traditional algorithms (such as PSO), the RL model significantly reduces the time consumption and improves the feature retention rate, which provides a more efficient feature extraction method for landscape planning.

(3) By using the subdivision strategy of adding points in the process of constrained triangulation, the set of straight lines in the triangular mesh is effectively guaranteed, and the similarity with the original curve is improved.

(4) The RL model reduces the number of calculations, improves the efficiency of terrain grid construction, and then reduces the time-consuming of superposition by eliminating the points that cannot form triangles.

(5) Compared with the traditional design method, the system can present the details and overall effect of landscape planning more accurately, and provide a superior visual experience.

This article begins by presenting the background and significance of environmental design and landscape planning, then posits the research impetus to integrate RL algorithms with CAD technology. Subsequently, it elaborates on the foundational principles and applications of CAD technology and RL algorithms within landscape planning. A comparative experiment is devised to assess the system's efficacy, contrasting the RL model against the PSO algorithm across three distinct landscape types. The results demonstrate the RL model's superiority in feature dimensionality reduction, terrain and landscape overlay precision, operational efficiency, and visual appeal. Lastly, the paper consolidates the research findings and underscores the application potential and dissemination worth of the system.

2 OVERVIEW OF CAD-AIDED LANDSCAPE PLANNING TECHNOLOGY

CAD is a design method using computer technology. It helps designers create, modify, analyze, and optimize the design scheme on the computer through special software, such as AutoCAD, SketchUp, and Rhino. The core of CAD technology lies in its powerful graphics processing ability and accurate data calculation ability, which enables designers to easily deal with complex geometric shapes, make accurate dimensioning, and quickly respond to design changes. In landscape planning, CAD technology is mainly used in terrain analysis, vegetation configuration, building layout, road design, and so on. Through CAD software, designers can easily draw contour lines and slope maps of terrain, help analyze terrain characteristics, and provide the basis for subsequent vegetation planting and architectural design.

In order to further explore the landscape planning of comprehensive sports venues and football fields, Li et al. [10] used GIS technology to compare and analyze the similarities and differences between the landscape design of comprehensive sports venues and football fields and that of general parks. In terms of handling methods and principles for special factors, Liu et al. [11] emphasized and integrated local historical and cultural characteristics, making sports facilities a part of urban culture. In the design process of complex sports venues and football fields, we have identified a series of special factors, including but not limited to venue size, functional diversity, audience capacity, competition requirements, safety regulations, and harmonious coexistence with the natural environment. By using CAD-assisted reinforcement learning decision systems, design points can be more accurately grasped, achieving a perfect integration of landscape effects and sports facility functions. This system not only improves design efficiency but also ensures the feasibility and sustainability of the design scheme.

Li et al. [12] addressed this challenge by proposing an innovative evaluation method that simulates real-world flood scenarios while outputting risk values and probabilities representing the safety and timeliness of each passable area. In addition, this article developed a groundbreaking path-planning algorithm based on deep reinforcement learning, which combines improved random reward utilization and heterogeneous reward exploration mechanisms to play a role in simulated rescue path-planning scenarios with uncertainty and complexity. A reinforcement learning decision system has been introduced on the CAD-assisted landscape planning platform, which can automatically analyze the potential impacts of design schemes, including visual effects, environmental benefits, cost-effectiveness, etc. This process not only improves design efficiency but also ensures the feasibility and innovation of the design scheme. Michalek et al. [13] combined the RGB feature decomposition method to conduct an in-depth analysis of landscape images, extract vectorized features of multidimensional nonlinear landscapes, and provide a basis for subsequent design optimization. Digital computer models are commonly used in landscape architecture, design and planning, and other related disciplines for visualizing proposals, evaluating alternative solutions, and simulating impacts. GIS systems create maps of landscape suitability and visibility, while CAD systems can create 3D renderings of road geometry or estimate cutting and filling volumes. Digital models refer to the intangible forms in computer memory that only appear in form or appearance during rendering, whether it is paper images or photos, computer screens, immersive display environments, or computer-generated physical models. Nie et al. [14] used differential equations and particle systems to describe the dynamic process of vegetation succession landscape. Many of them are related to realism, but not limited to visual photographs. In order to model and visualize landscapes, a balance needs to be sought between "looking like" and "behaving like". Currently, in the digital environment, interactive landscapes are more commonly used in public spaces such as squares, residential areas, and parks. As the world's rapidly developing second-largest economy, China has achieved remarkable results in the innovation speed created by digital technology, providing design practitioners with more updated development paths. Therefore, Zhang and Deng [15] take digital concepts as the research foundation, and the combination of interactive design and landscape design in commercial spaces is an important aspect of their research. However, there are relatively few public spaces and commercial pedestrian streets around commercial complexes, and related concepts are still in their infancy. Overall, there is a lack of theoretical research and specific practice on the application of interactive technology to commercial space landscape design.

3 LANDSCAPE PLANNING DECISIONS BASED ON CAD AND RL

This data-driven decision-making method can reduce the interference of human factors, improve the objectivity and accuracy of decision-making, and gradually accumulate design experience through continuous learning.

In the construction of a complex layout optimization framework, a lightweight and efficient clipping model is selected. Based on the aesthetic assessment of images, the model uses a deep neural network to extract the saliency map, locates the anchor frame through the target integrity constraint, and then learns the relationship between the target and the aesthetic area through a regression network to quickly determine the best clipping rectangle, which significantly improves the calculation efficiency and accuracy. The cutting process is shown in Figure 1.

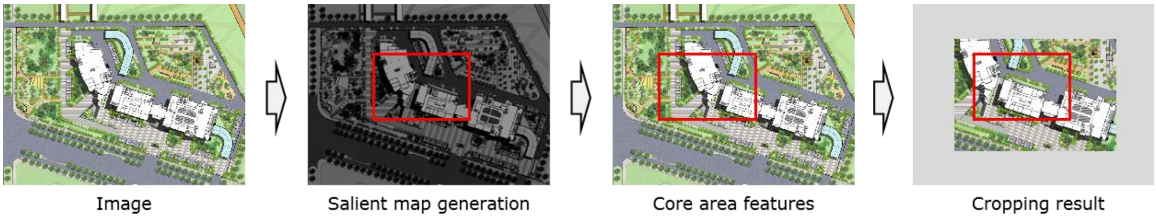

Figure 1: Cutting model based on aesthetic assessment.

The method for calculating the boundary M of landscape function type C_j is outlined below:

$$\beta_0, \beta = \arg\max C_j \quad where Y_j\left(\beta_0 + \sum_i \beta_i y_{ij}\right) \geq C_j \tag{1}$$

The formula β_0, β serves as both a constant and a weighted variable for determining the landscape's functional characteristics y_{ij} while Y_j denoting the classification of these functional types. The precision of identifying landscape functional zones is validated. Utilizing the confusion matrix, the precision is assessed through quantitative metrics, focusing on overall accuracy and the specific types of functional zones. The Kappa coefficient formula is employed for recognizing these functional areas:

$$K = \frac{P_o - P_e}{1 - P_e} \tag{2}$$

Here P_o represents the proportion of accurately classified samples within each function type relative to the total sample count, while P_e signifies the ratio of the product of the actual count of each function type and the number of its classified samples, divided by the square of the total sample size.

Combining CAD with the RL decision system is necessary to build an intelligent landscape planning platform. This platform should have the following key functions:

(1) Data integration and management: The platform needs to be able to integrate design data such as topography, vegetation, and buildings generated by CAD design software, as well as external information such as historical project data and user feedback.

(2)RL model construction: On the basis of data integration, the platform needs to build an RL model. This model should be able to automatically explore and optimize the design scheme according to the design objectives (such as ecological balance, cultural heritage, economic benefits, etc.) and constraints (such as terrain characteristics, vegetation distribution, building codes, etc.).

(3) Intelligent decision support: The optimized scheme generated by the RL model needs to be presented to designers in an intuitive and easy-to-understand way. The platform should provide rich visualization tools to help designers quickly understand the effect of the scheme.

(4) Collaborative design and feedback cycle: An intelligent landscape planning platform should support multi-person collaborative design to ensure that designers with different professional backgrounds can communicate and collaborate efficiently.

If the grid's side length in the X direction is N and in the M,Y direction, then:

$$i = \text{int}\ X / M \tag{3}$$

$$j = \text{int}\ Y / N \tag{4}$$

In this context, int represents integer operations. The grid label assigned to the point X,Y consists of the grid formed by four points, designated as i,j , $i+1,j$, $i+1,j+1$, $i,j+1$.

Based on the coordinates of the above four-point elevation values $Z_{ij}, Z_{i+1}, Z_{i+1,j+1}, Z_{i,j+1}$ and point $P'\ X,Y$ in the grid, the point $P'\ X,Y$ elevation value Z can be obtained by interpolation calculation.

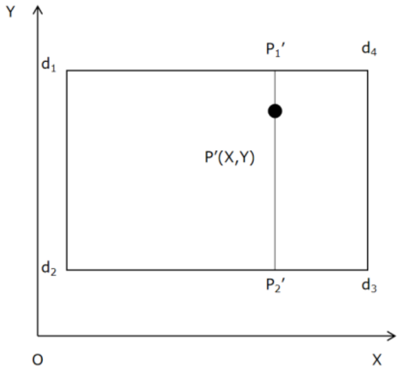

Figure 2: P' point elevation.

In Figure 2, the spatial coordinates of grid sites are defined as $d_1\ X_i, Y_j, Z_{ij}$, $d_2\ X_{i+1}, Y_j, Z_{i+1,j}$, $d_3\ X_i, Y_{j+1}, Z_{i,j+1}$ and $d_4\ X_{i+1}, Y_{j+1}, Z_{i+1,j+1}$. Assume that λ_1 represents the influence parameter of elevation calculation:

$$\lambda_1 = (X - X_i) / (X_{i+1} - X_i) \tag{5}$$

Then, the elevation expression of the point P'_1 is:

$$Z_1 = \lambda_1 \cdot Z_{ij} + (1 - \lambda_1) \cdot Z_{i+1,j} \tag{6}$$

Where the elevation expression of the point N_{new} P'_2 is:

$$Z_2 = \lambda_1 \cdot Z_{i,j+1} + (1 - \lambda_1) \cdot Z_{i+1,j+1} \tag{7}$$

According to $\lambda_2 = (Y - Y_j) / (Y_{j+1} - Y_j)$, the elevation expression of P' the point is obtained:

$$Z = \lambda_2 \cdot Z_1 + (1 - \lambda_2) \cdot Z_2 \tag{8}$$

Mark the 3D dynamic symbol of the point factor in the constructed terrain grid at the position of the point $P'(X, Y, Z)$.

In the RL algorithm, the state is information describing the current situation of the environment. In landscape planning, the state can include topographic features, vegetation distribution, building location, and so on. This state information can be extracted and expressed by CAD software as the input of the RL algorithm. Actions can include adjusting the species and layout of vegetation, changing the location and shape of buildings, optimizing road design, etc. These actions can be realized by the editing function of CAD software and used as the output of the RL algorithm.

During RL model training, the loss function quantifies the discrepancy between predicted and actual values. It is defined using the formula:

$$L = \frac{1}{N} \sum_{i=1}^{N} \gamma (y_i, \hat{y}_i) \tag{9}$$

Here, L denotes the loss function, N the total sample count, y_i the true value, $\hat{y}_i$ and the predicted value and γ specifies the type of loss function; examples include mean square error or cross-entropy loss.

CAD software employs iterative optimization to enhance the design progressively:

$$x_{n+1} = x_n + \alpha \cdot \nabla_x F(x_n) \tag{10}$$

Here x_{n+1} signifies the next state iteration, x_n the current state, a the learning rate, and $\nabla_x F(x_n)$ the gradient of the objective function $F(x)$ assessed at the current state x_n .

According to the current state information, the policy network can generate the optimal action sequence, that is, the design scheme. Through continuous training and optimization, the strategic network can gradually learn how to take optimal action in different States. In the training process, the RL algorithm will constantly try different actions and assess its effect according to the reward function. Through continuous iteration and optimization, the strategy network will gradually converge to the optimal solution, that is, the optimal design scheme will be generated.

On the intelligent landscape planning platform, the decision based on CAD and RL can be summarized as the following steps:

(1) Clear design objectives and constraints: Designers first need to clear the design objectives and constraints of landscape planning.

(2) Data preparation and integration: according to the design objectives and constraints, collect and sort out relevant design data.

(4) Model training and optimization: On the basis of data integration, the RL model is trained. The learning process of the model is an iterative and continuous optimization process.

(5) Decision Support and Scheme Presentation: When the RL model is trained, it can provide designers with an optimized design scheme.

(6) Collaborative design and feedback collection: In the decision-making process, designers can collaborate with team members to improve the scheme together.

To create a highly realistic 3D landscape model, restoring details like scene layout is crucial. Utilizing an object detection algorithm identifies building elements, and their layout structure is estimated from detection outcomes. Initially, 3D objects are projected onto a 2D plane, and the layout is adjusted to find the best configuration. For individual scene objects, the objective function aims to:

$$\min_{H} k = 1 - L\left(h, O\left(H, l, P\right)\right) \tag{11}$$

In 2D space, $L(\cdot)$ denotes the overlap probability of two regions, h the detection outcome, $O(\cdot)B$ and the projection function, while in 3D space, H signifies object data and l object rotation data. For scenes with multiple objects, both individual 2D detection results and their spatial overlaps must be accounted for. The spatial arrangement objective for these objects is formulated as:

$$\min_{H} k = \sum_{i}\left(1 - L\left(h_i, O\left(H_i, l_i, P\right)\right)\right) + \varpi \sum_{m,n} L\left(H_m, H_n\right) \tag{12}$$

Where $\sum_{i}\left(1 - L\left(h_i, O\left(H_i, l_i, P\right)\right)\right)$ represents the deviation of each object from the detection result of the objective function in the 2D space; $\varpi \sum_{m,n} L\left(H_m, H_n\right)$ represents the overlapping probability of two objects in 3D space. Adjusting parameters ϖ ensures non-overlapping objects in 3D space, adhering to real-world physical principles. An optimization method is devised to enhance object layout accuracy in the building. Utilizing 2D space information, the landscape space bounding box generates more precise data, formulated as:

$$\frac{q_k^i}{r_k^i} = \frac{q_s^i}{r_s^i} \tag{13}$$

Here q_k^i and r_k^i signify the length and width of the i object in 2D space, while q_s^i and r_s^i represent the dimensions of the i object's scene space bounding box. Target detection yields object categories and quantities, with object type initialization expressed as:

$$\widehat{W}_i \in \left\{V_{z_i}^1, V_{z_i}^2, V_{z_i}^3, \ldots, V_{z_i}^n\right\} \tag{14}$$

Where $\widehat{W}_i$ is the volume information of the i th object; $V_{z_i}^n$ represents the n model when the category is z_i. A more accurate and realistic model can be obtained by fine-tuning the layout of objects in 3D space.

4 EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Experimental Purpose and Setting

The main purpose of the experiment is to compare and analyze the comprehensive performance of the RL model and PSO algorithm in the field of landscape planning, especially in three key aspects: feature dimension reduction, terrain and landscape overlay accuracy and operation efficiency. In order to assess the advantages and disadvantages of the two methods comprehensively and accurately, three representative landscape types-functional landscape, ecological landscape and cultural landscape-were selected as the test objects of the experiment. These three landscape types not only cover the main application fields of landscape planning but also have their own unique characteristics and planning requirements.

In the functional landscape, the practicality and functionality of the landscape are emphasized, such as the design of public spaces such as parks and squares. This kind of landscape needs to meet people's activity needs while ensuring beauty. In the ecological landscape, the importance of ecological protection and restoration is emphasized, such as the planning of natural landscapes such as wetlands and forests. This kind of landscape requires full consideration of ecological balance and biodiversity in the design process. In the cultural landscape, attention is paid to the inheritance and performance of history and culture, such as the planning of historical sites, cultural heritage and other scenic spots. This kind of landscape requires full integration of local cultural elements in design.

In order to ensure the fairness and comparability of the experiment, the experimental conditions are strictly controlled. All experiments are carried out under the same hardware environment and software configuration, which avoids experimental errors caused by equipment differences. Furthermore, the experimental data are strictly preprocessed and verified to ensure the reliability of the data. During the experiment, the same assessment index and method are adopted, and the performance of the RL model and PSO algorithm is comprehensively and objectively compared and analyzed.

4.2 Comparison of Feature Dimension Reduction Effects

In the aspect of feature dimensionality reduction, the RL model and PSO algorithm are used to reduce the dimensions of three landscape types, and the dimensionality reduction time and feature retention rate are recorded. The results show that the RL model is significantly shorter than the PSO algorithm in dimensionality reduction time (about 60% of PSO), and the feature retention rate is also improved by about 10%. This result proves the advantages of the RL model in feature dimension reduction, which can extract landscape features more efficiently while retaining more key information.

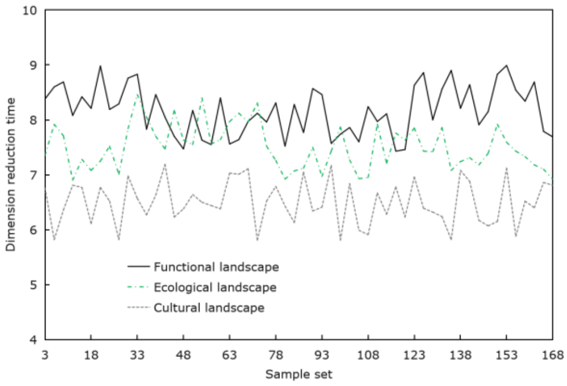

Figure 3: Dimension reduction time of PSO algorithm.

Figure 3 displays the lengthy dimension reduction time of the PSO algorithm, whereas Figure 4 showcases the significantly shorter time achieved by the RL model.

4.3 Comparison of Terrain Landscape Overlay Accuracy

In the aspect of terrain and landscape overlay, the overlay accuracy of the RL model, PSO algorithm and traditional design method are compared.

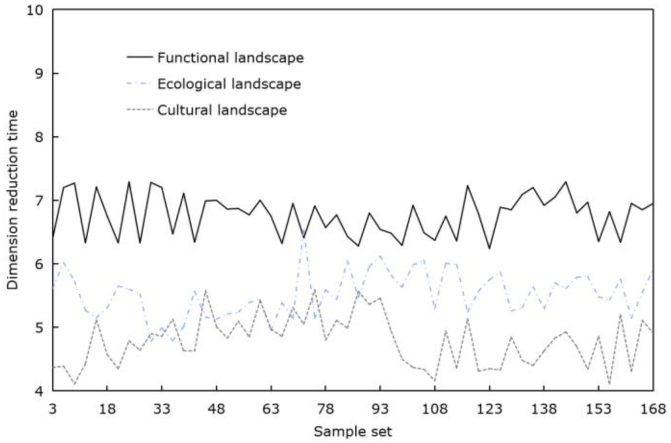

Figure 4: Dimension reduction time of RL model.

The results show that the RL model has the highest fitting degree with the actual situation, which indicates that the terrain and landscape overlay algorithm has high accuracy and strong reliability. This is mainly due to the strategy of adding points and subdivision used by the RL model in the process of constrained triangulation, which effectively ensures that there is a set of straight lines in the triangular mesh, and improves the similarity between the original set of straight lines and the original curve, thus initially enhancing the accuracy of the algorithm.

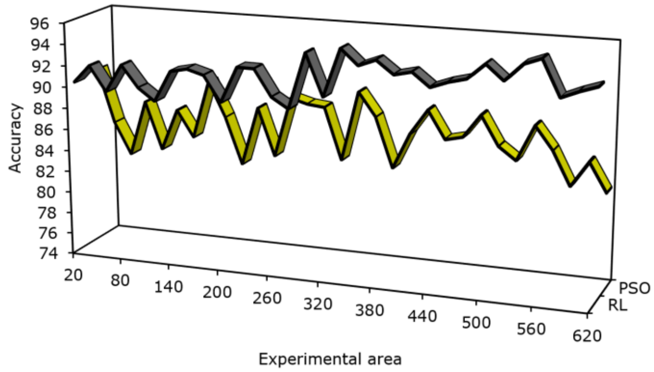

Figure 5: Accuracy comparison of different methods.

Figure 5 shows the accuracy comparison of different methods, and the advantages of the RL model in stacking accuracy can be clearly seen. In addition, by using three terrain factors, namely point, line, and surface, the RL model further improves the stacking accuracy and shows its robustness to some extent.

4.4 Comparison of Operation Efficiency

In the aspect of running efficiency, the running time of the RL model and PSO algorithm in different areas is compared. The results show that the RL model has a good running efficiency. This is mainly due to the fact that the RL model eliminates the points that cannot form triangles when constructing a terrain landscape grid, thus reducing the number of calculations and improving the efficiency of terrain grid construction.

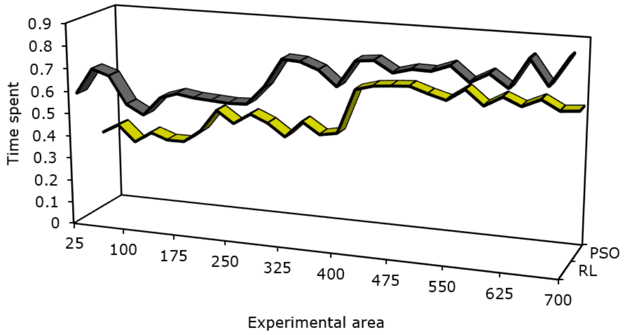

Figure 6: Comparison of running time of different methods.

Figure 6 shows the running time-consuming comparison of different methods, and the advantages of the RL model in running efficiency can be seen intuitively. This result proves the potential and application value of the RL model in dealing with large-scale landscape planning tasks. Finally, the traditional design method and RL model are compared in the visualization effect of landscape environment planning. The results show that the visualization effect of the RL model is superior, and it can present the details and overall effect of landscape planning more accurately.

Figure 7: Visualization effect of traditional design method.

Figure 7 shows the visualization effect of the traditional design method, and it can be seen that it has some shortcomings in detail presentation and overall coordination.

5 CONCLUSIONS

Firstly, the limitations of traditional CAD in landscape planning are analyzed, and then an innovative idea of combining the RL algorithm with CAD technology is put forward. By constructing the decision model of landscape planning based on CAD and RL, the automatic optimization of the design scheme is realized, and the design efficiency and quality are greatly improved.

By comparing the performance of the RL model and PSO algorithm in three different types of landscapes, the experimental part fully proves the advantages of the RL model in feature dimension reduction, terrain and landscape overlay accuracy and operation efficiency. Especially in feature dimensionality reduction, the RL model significantly reduces time consumption and improves the feature retention rate. In the accuracy of terrain and landscape overlay, the results obtained by the RL model have the highest fitting degree with the actual situation, which shows its high reliability and accuracy. In terms of operational efficiency, the RL model shows good performance, which provides strong support for dealing with large-scale landscape planning tasks. In addition, the superiority of the RL model in landscape environmental planning is further verified by the comparison of visual effects.

To sum up, CAD-aided landscape planning and RL decision-making systems in environmental design provide a new method for landscape planning. In the future, with the deepening of research, it is believed that the system will play a more important role in urban environmental design.

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