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Building Performance Prediction Model Using CAD Technology and Recurrent Neural Networks

Nian Wu[1] and Zhao Ye[2]

[1]School of Architectural Engineering, Shanghai Zhongqiao Vocational and Technical University, Shanghai 201514, China, wunian@shzq.edu.cn
[2]School of Architectural Engineering, Shanghai Zhongqiao Vocational and Technical University, Shanghai 201514, China, yezhao@shzq.edu.cn

Corresponding author: Nian Wu, wunian@shzq.edu.cn

Abstract. Due to the continuous progress of technology, researchers and engineers are exploring various new methods and technologies. In this article, recurrent neural network(RNN) is used to build a prediction model of building performance, and it is combined with computer-aided design (CAD) technology to improve the building design method. The model can adapt to different types of buildings and performance indicators and improve the accuracy of prediction. RNN model has obvious advantages in prediction accuracy and operation efficiency. This is due to the fact that the RNN model can capture the time dependence and correlation between building performance parameters so as to predict future performance more accurately. Through real-time feedback and automatic optimization, designers can find and solve potential performance problems early and reduce the cost of later modification and rework. Combining CAD technology with RNN is of practical significance to the building design industry, promoting the industry to develop more efficiently and sustainably.

Keywords: CAD; Recurrent Neural Network; Building Performance Prediction
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1 INTRODUCTION

In today's construction industry, it has become more and more important to predict the performance of buildings accurately. Researchers and engineers are exploring various new methods and technologies to improve the efficiency of building design. Architectural design is a process that requires comprehensive consideration of multiple factors, including functional needs, aesthetic needs, environmental needs, etc. Traditional architectural design methods often rely on the experience and intuition of designers, making it difficult to explore diverse solutions. Recurrent neural networks are gradually being applied in architectural design. Berseth et al. [1] adjust the size, shape, and layout of buildings through parametric design. For example, they are changing the size or position of windows or adjusting the thickness of walls. It collects a large amount of architectural design images or 3D model data. These data can include various architectural design styles, layouts, and details. Then, the design principles and implementation process of interactive architectural design based on CAD technology and recurrent neural networks were elaborated in detail. Finally, conclusions and prospects were proposed. Using recursive neural networks to learn data and establish a predictive model for architectural design schemes. This model can predict indicators such as effectiveness, cost, and feasibility of different design schemes. Design an interactive interface based on CAD technology, allowing users to adjust and optimize the design scheme. The interface should be intuitive and easy to operate so that users can easily explore different design solutions. RNN and CAD technology are two technologies with broad application prospects. This article will discuss how to use CAD technology and RNN to build a building performance prediction model to improve the building design method. Machine learning algorithms such as recurrent neural networks are gradually being applied to interior architectural design, providing designers with more design possibilities. Denerel and Anil [2] discussed how to use CAD technology and recurrent neural networks to implement. In the design process, designers can use CAD software to measure and locate various elements accurately to ensure the accuracy and consistency of the design. In addition, CAD software can also provide powerful drawing and editing functions so that designers can easily design and edit complex geometric shapes and improve the complexity and diversity of design. Machine learning algorithms such as recurrent neural networks are gradually being applied to interior architectural design, providing designers with more design possibilities. This article will explore how to use CAD technology and recurrent neural networks to implement.

The field of architectural design has entered the era of BIM. BIM is a digital method that utilizes computer technology for architectural design, construction, and management, which can significantly improve design efficiency and quality. However, traditional BIM methods often rely on centralized servers and databases, which pose issues of data security and privacy protection. To address these issues, Dounas et al. [3] conducted a study. A decentralized BIM framework for architectural design was proposed using CAD technology, recurrent neural networks, and blockchain technology. Recurrent neural networks are powerful machine learning algorithms that can be used to process sequential data. In architectural design, recurrent neural networks can be used for automated design, style recognition and classification, spatial planning and optimization, and more. Create a 3D model of the building using CAD technology and convert it into a BIM model. Using recursive neural networks to learn BIM models and predict performance and cost indicators for different design schemes. Using blockchain technology to build a decentralized architectural design platform, storing BIM models and related data in a distributed database. Implementing automated design and construction management through smart contracts to ensure data security and credibility. Today's people live in a data-driven era, and big data technology is changing the way many industries operate. The construction industry is no exception; from the initial planning and design to the construction and operation stages, data plays a vital role. In this context, there is an urgent need to analyze and process these data by using artificial intelligence (AI) technology. As a powerful tool for processing sequence data, RNN has been proven to have excellent performance in many fields. Therefore, the application of RNN in building performance prediction has great potential. Architectural design is a process that requires comprehensive consideration of multiple factors, including functional needs, aesthetic needs, environmental needs, etc. Traditional architectural design methods often rely on the experience and intuition of designers, making it difficult to explore diverse solutions. Such as recurrent neural networks are gradually being applied in architectural design. Entezari et al. [4] explored how to use CAD technology and recurrent neural networks to achieve architectural design control functions. Through CAD technology, designers can parameterize architectural design by adjusting parameters to change the design scheme. Automated design tools can quickly generate diverse design solutions. By learning and analyzing a large amount of design data, these tools can automatically generate design solutions that meet the requirements of designers. Designers can choose the most suitable design scheme based on their own needs and preferences, thereby saving a lot of time and energy. Secondly, automated design tools can improve the accuracy and quality of design. These tools utilize the precise measurement and positioning capabilities of CAD technology to ensure consistency and accuracy in design solutions. Meanwhile, they can also optimize and improve design schemes through machine learning and artificial intelligence algorithms, enhancing the overall quality and effectiveness of the design. By training a recursive neural network model, it is possible to predict the spatial effects and user satisfaction of different layout schemes, providing decision support for designers. A model based on recurrent neural networks can automatically generate design suggestions based on user needs and historical data, improving design efficiency and quality. However, traditional CAD software mainly focuses on the design of geometry and aesthetics, but it is relatively weak in predicting the performance of buildings. Therefore, the combination of RNN and CAD technology is expected to make up for this deficiency, thus improving the comprehensive performance of building design.

The construction of offshore building structures is a complex and challenging task that requires careful consideration of multiple factors, such as marine environment, structural design, construction methods, etc. The traditional construction methods of offshore structures often rely on experience and trial and error, making it difficult to achieve efficient and accurate design and construction. CAD and recurrent have gradually been applied in the construction of offshore building structures, providing new ideas and methods for the design and construction of offshore building structures. Han et al. [5] explored the application of CAD technology and recurrent neural networks. Recurrent neural networks are powerful machine learning algorithms that use time series prediction. In the construction of offshore building structures, recurrent neural network performance and behaviour better understand structural characteristics and optimize them. Augmented, allowing users to intuitively observe and understand the design and construction process of offshore building structures. Through augmented/virtual reality technology, designers can communicate and collaborate in real time with clients, construction parties, etc., improving the efficiency and accuracy of design and construction. This article will discuss the application of RNN and CAD technology in building performance prediction. Moreover, it will also study how to combine CAD technology with RNN to realize the automation of the building design process. The research results will provide practical tools for the building design industry and help architects of buildings more accurately. This will reduce the cost of buildings, improve the service life of buildings and promote the sustainable growth of the construction industry. Combining RNN with CAD technology it is expected to develop a more intelligent building design system and provide architects with more convenient design tools. Specifically, the research has the following innovations:

(1) In this article, RNN and CAD technology are combined and applied to building performance prediction. This interdisciplinary research method provides a new perspective and tool for building design.

(2) This article constructs a more general and efficient building performance prediction model. The model can adapt to different types of buildings and performance indicators.

(3) By directly extracting building information from CAD drawings and inputting it into the RNN model, the risk of data conversion and information loss is reduced, and the performance of prediction is improved.

(4) By introducing visualization technology, such as the attention mechanism, we can better understand the basis and process of model prediction and improve the credibility of the model. Then, the construction and training of the RNN model and the comparison with the support vector machine (SVM) method are described. Then, the comparison results of algorithm performance indexes are analyzed, and the advantages of this method are highlighted. Finally, it summarizes the full text and puts forward the development direction of the construction industry.

2 RELATED WORK

Mathematical principles quantitatively analyze various factors in the architectural design process by introducing nonlinear mathematical functions and algorithms and generating architectural design schemes with unique spatial forms through computer simulation and optimization. This method breaks through the limitations of traditional linear design and provides architects with more design possibilities. Hu et al. [6] Nonlinear design is an important direction of modern landscape architecture design. This design method emphasizes the dynamics and variability of the design and can better adapt to the complex and changing environment and needs than the traditional linear design method. CAD big data can help designers better understand and simulate nonlinear design, for example, by simulating the impact of natural factors such as water flow and wind on the landscape. Based on CAD data and mathematical principles, establish a mathematical model for digital nonlinear landscape architecture design and verify and optimize the design scheme through computer simulation technology. By utilizing digital nonlinear design methods and techniques, unique and artistic architectural spatial forms can be created, enhancing the aesthetic value and practicality of the building. However, traditional CAD methods often only achieve single-objective optimization and cannot meet complex multi-objective optimization problems. Therefore, how to achieve automatic design of computer architecture structures for multi-objective optimization has become a hot research topic. Latif and Ismail [7] explored the method of space hyperheuristic exploration for the automatic design of computer architecture structures for multi-objective optimization. By introducing the basic principle of the heuristic search algorithm and its application in the automatic design of building structures, a method for the automatic design of building structures based on the heuristic search algorithm is proposed and experimentally verified. Super heuristic search heuristic search which guides the search process by introducing some heuristic rules, thereby accelerating search speed and improving search quality. In the automatic design of building structures, hyperheuristic search algorithms can be used to find the optimal design solution to achieve optimal solutions for multiple objectives. The design method for building structures based on a heuristic search algorithm can effectively find the optimal design solution and perform well in multiple objective optimization problems. Compared with traditional CAD methods, this method has higher efficiency and better robustness.

Roman et al. [8] explored how to integrate the data flow of the lifecycle using CAD technology and recurrent neural networks. Firstly, the basic concepts of the construction project lifecycle, CAD technology, and recurrent neural networks were introduced, along with their applications in building information modelling. Then, the implementation process of building information modelling for digital enterprises based on these technologies was elaborated in detail, including data flow integration, information model construction, automation design, etc. Finally, conclusions and prospects were proposed. The lifecycle of a construction project is a complex process that involves multiple stages and stakeholders. In building information modelling, it is necessary to integrate and share data from various stages in order to better manage and optimize the project. CAD technology is a computer-aided design tool that can help designers quickly and accurately create and modify architectural design schemes. In building information modelling, CAD technology can be used to establish 3D models and perform parametric design, automated design, and other aspects. By integrating the data flow of the construction project lifecycle and establishing a digital enterprise based on CAD technology and recursive neural networks for building information modelling, comprehensive digital management and operation of projects can be achieved. This includes project management, resource management, quality management, and other aspects to improve the overall efficiency and effectiveness of the project. Traditional BIM methods can only achieve two-dimensional modelling and display and cannot meet complex three-dimensional spatial requirements. Safikhani et al. [9] input the data of the CAD model into the recurrent neural network. Neural networks can learn the characteristics and laws of buildings and generate new architectural design schemes. CAD technology can provide accurate building models and provide data input for recurrent neural networks. Recurrent neural networks can generate a variety of design schemes, providing more options for immersive virtual architecture reality technology. The immersive virtual building reality technology can provide designers and the public with a more intuitive and vivid experience. Then, the design principles and implementation process of immersive virtual reality technology based on CAD technology and recurrent neural networks were elaborated in detail. Finally, conclusions and prospects were proposed. Through immersive virtual reality technology, users can view and experience architectural design schemes in three-dimensional space, such as adjusting materials, colours, and lighting, and view design effects in real time. Through immersive virtual reality technology, designers from different regions can collaborate on architectural design in virtual spaces, improving team collaboration efficiency.

With the acceleration of urbanization, effective and efficient urban planning and design have become crucial. Urban Information Modeling (CIM) is a multidisciplinary approach aimed at creating and maintaining digital representations of urban environments. Digital urban design utilizes advanced technological tools and methods to optimize the urban design process. In this process, CAD technology and recurrent neural networks are playing an increasingly important role. Stojanovski et al. [10] briefly introduced the concepts of CIM and digital urban design and then elaborated on how CAD technology and recurrent neural networks can be combined and applied to these fields in detail. CAD technology provides powerful tools for urban information modelling, which can accurately represent the physical and functional features of cities. Through CAD software, designers can create complex city models, including buildings, roads, public facilities, etc., to support better decision-making and planning. In digital urban design, CAD technology can be used not only for modelling and visualization but also for supporting performance simulation and analysis, such as traffic flow, environmental impact, etc. This helps designers identify and resolve potential issues before project implementation. Traditional 3D modelling and image processing techniques are time-consuming and have limited accuracy. In recent years, advances have been widely applied in 3D modelling, providing more efficient and accurate methods for creating virtual building environments. Tytarenko et al. [11] explored technology and Recurrent Neural Networks (RNNs) for 3D modelling of virtual building environments and studied fortresses as a case study. The technology and RNN in 3D modelling are then elaborated on, and the fortress 3D modelling process is based on these technologies, including data collection, model construction, optimization, and validation. Finally, the effectiveness and practicality of this method were demonstrated through experimental results. Using CAD technology, fortress based on the collected data. By precise geometric modelling and texture mapping, the model is made highly realistic. Optimize the model using recursive neural networks. By training the RNN model to learn the structural features and details of the fortress, the accuracy of the model can be further improved. At the same time, historical photos and terrain information are used for verification to ensure the accuracy of the model. Based on the optimized 3D model, real-time rendering technology is used to visualize the virtual building environment. Users can freely roam in the virtual environment and interact with the model, achieving an immersive experience.

The application of point cloud data in fields such as architecture and urban planning is becoming increasingly widespread. However, registering point cloud data with CAD drawings is a challenging issue, especially for low-cost digital twin buildings, where registration is more difficult due to relatively low data quality and accuracy. Therefore, studying an efficient and accurate registration method has important practical significance. Wu et al. [12] proposed a symmetry-based method for rough registration of point cloud data. This method utilizes the symmetry features of buildings to automatically align point cloud data with CAD drawings by identifying and matching symmetric elements. The article first introduces the background and significance of point cloud registration and digital twins and then elaborates on the principle and implementation process of symmetry-based registration methods. Finally, the effectiveness and practicality of this method were verified through experimental results. The stable registration results in different scenarios and data quality and has high registration accuracy and efficiency. Compared with traditional methods and deep learning-based methods, our method has lower computational costs and higher practicality. With the acceleration of urbanization and the increasing demand for living environment quality, intelligent building design has become an important development direction in the construction industry. Intelligent building design needs to consider numerous factors, including human behaviour, building performance, environmental factors, etc. In order to better address these complex factors. Yi [13] proposed an agent-based model for simulation. This model adopts a visual collaborative simulation method, which comprehensively considers various factors such as human behaviour, building performance, and environmental factors, providing an effective decision-support tool for intelligent building design. Visual collaborative simulation is a method that combines simulation processes with visualization techniques. In intelligent building design, visual collaborative simulation can present building design schemes in an intuitive way, facilitating designers' decision-making. Meanwhile, through collaborative simulation, designers can collaborate with various experts to explore design solutions and achieve better architectural design.

Colour, as an indispensable element in architectural landscape design, has been more accurately and deeply explored for its effects in computer-aided collaborative design systems. Zhang and Deng [14] discussed the application of effects in architectural landscape design. By elaborating on the development and characteristics of computer-aided collaborative design systems, as well as their application in architectural landscape design, this paper further explores the importance of colour effects in architectural landscape design and proposes methods for optimizing colour effects using computer-aided collaborative design systems, which has a profound impact on human psychology and physiology. Colour effects include physiological, psychological, and cultural effects of colour. In architectural landscape design, the reasonable use of colour effects can enhance the visual impact of the design and create a unique atmosphere and emotions. With the increasing scarcity of global energy resources, energy-saving design has become an important development direction in the field of architecture. CAD technology. Recurrent neural networks, as a powerful machine learning algorithm, can help designers better understand and optimize building energy-saving design. Zhao [15] explores how to apply CAD technology and recurrent neural networks in building energy-saving designs. Explored how to apply CAD technology and recurrent neural networks in building energy-saving designs. Firstly, the basic concepts of CAD technology and recurrent neural networks were introduced, followed by a detailed explanation of their application process and results in building energy-saving designs. Finally, conclusions and prospects were proposed. Through CAD technology, designers can optimize architectural design, including adjusting the layout of the building, material selection, window design, etc. This helps buildings and improves their energy efficiency. By utilizing the simulation function of CAD technology, designers can conduct simulation analysis on building design to predict the energy consumption and thermal performance of the building. And adjust the design plan in a timely manner, thereby improving the energy efficiency of the building.

These research results show a variety of methods and application scenarios for building performance prediction using AI and provide practical tools and ideas for the building design industry. However, these studies are often limited to specific building types or performance indicators, and there are also some limitations in model construction and optimization. Therefore, this article aims to build a more general and efficient building performance prediction model to adapt to various types of buildings and performance indicators. Moreover, by combining CAD technology, a more intuitive and convenient building design method is realized.

3 RELATED TECHNICAL BASIS

3.1 Recurrent Neural Network (RNN)

Different from the traditional feedforward neural network, RNN has a circular structure, which can transmit the information from the previous moment to the next moment, thus capturing the time dependence in the sequence data. Therefore, RNN is very suitable for processing data with time series relationships.

In RNN, the hidden state of each moment is the hidden state of the previous moment. This structure enables RNN to capture long-term dependencies in sequence data. In building performance prediction, RNN can be used to process various time series data, such as climate change, lighting conditions, personnel activities, etc., to predict building performance indicators such as energy consumption and comfort.

3.2 Computer-Aided Design (CAD)

CAD technology is a design technology using a computer system. CAD software can help architects to design more efficiently and reduce mistakes to some extent. By using CAD software, architects can create and modify geometric shapes, conduct spatial analysis and generate construction drawings.

Traditional CAD software mainly focuses on geometric and aesthetic design, but it is relatively weak in predicting building performance. In order to make up for this deficiency, researchers are exploring ways to combine CAD technology with AI technology. By combining the geometric information of building design with the performance prediction model, the performance of buildings can be predicted more accurately and optimized in the design process. CAD technology can provide information such as geometric shape, material properties and spatial layout of buildings, and performance prediction models can use this information to predict performance indicators such as energy consumption and comfort of buildings.

CAD technology can provide information such as the initial design scheme and spatial layout of buildings as input data to RNN for training and learning. The input data is used to generate a new design scheme or improve the original scheme.

4 BUILDING PERFORMANCE PREDICTION MODEL BASED ON RNN

RNN has been widely used in the processing and analysis of various sequence data because of its unique cyclic structure. The core architecture of building a performance prediction model based on RNN is mainly composed of an input layer, an RNN layer, and an output layer. The input layer is responsible for receiving relevant time series data, such as climate data and personnel activity data. These data will first go through a preprocessing stage, including data cleaning, normalization, and other operations to ensure the accuracy and consistency of the data.

The RNN layer is the core part of the model, which is responsible for capturing the time dependence in the input data. In order to overcome the problems of traditional RNNs in processing long sequence data, we choose to use LSTM or GRU as the concrete implementation of the RNN layer. These improved RNN structures can learn long-term dependence more effectively by introducing a gating mechanism and memory unit, thus improving the prediction performance of the model. The output layer is responsible for converting the output of the RNN layer into specific predicted values of building performance indicators. According to the specific prediction task, the output layer can adopt different structures and activation functions. For example, for an energy consumption forecasting task, we can use a linear activation function; For comfort prediction tasks, a softmax activation function can be used for classification. The system learning architecture based on RNN is shown in Figure 1.

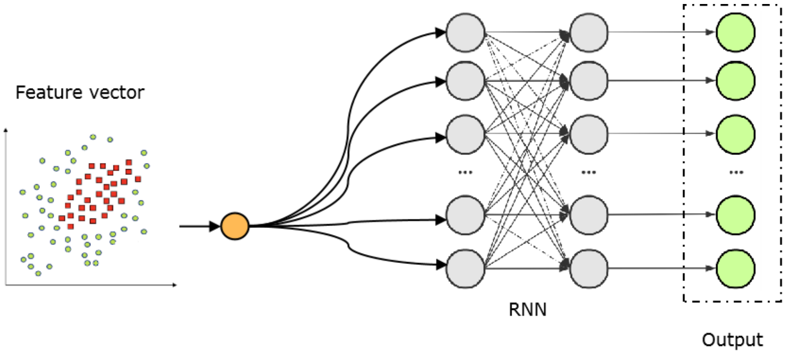

Figure 1: System learning architecture.

RNNs produce an output at every time step, characterized by a cyclic connection within their hidden units. Alternatively, this circular connection can be visualized as extending from the output of the preceding time step to the hidden unit of the present time step. Consistent with this structure, each time step aligns with a single input. The equation governing the network's forward propagation during the update process takes the following form:

$$a_t = b + Wh_{t-1} + Ux_t \tag{1}$$

$$h_t = \tanh(a_t) \tag{2}$$

$$o_t = c + Vh_t \tag{3}$$

$$\hat{y}_t = soft\max(o_t) \tag{4}$$

The weight matrix U,W and the offset vector b are associated with the connections feeding into the hidden unit, whereas the weight matrix V and the offset vector c pertain to the connections linking this time step to the subsequent one within the hidden unit. Serving as an intermediary between past and future information, the hidden unit h disentangles the interdependence between past and future, thereby enabling variables separated by a considerable distance to indirectly influence the network's output through their impact h.

In order to train and optimize the building performance prediction model based on RNN, a large quantity of high-quality time series data is needed. These data come from various sensors, monitoring systems or simulation software. The operation flow of RNN is shown in Figure 2.

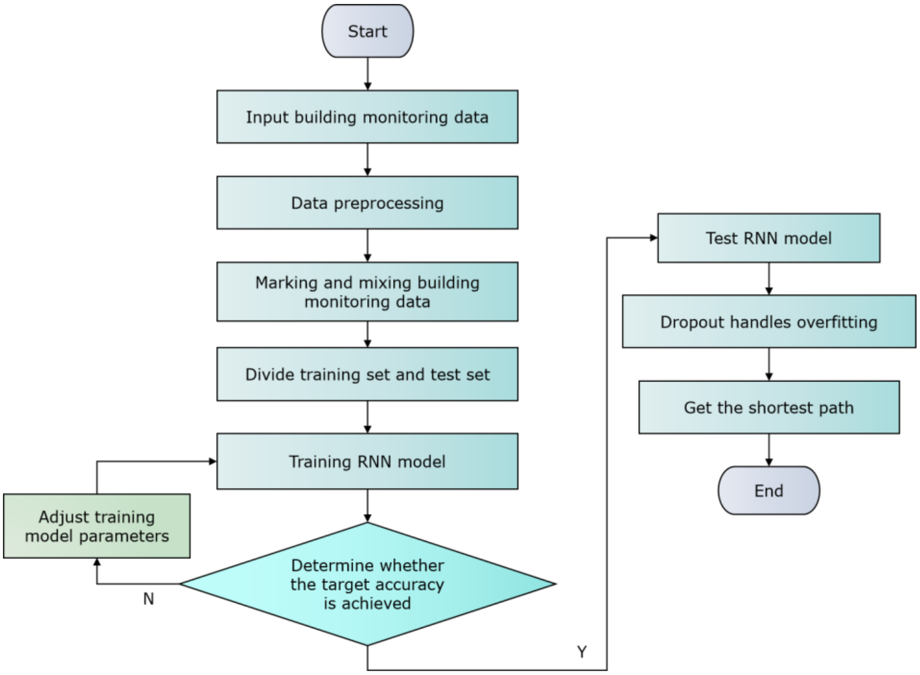

Figure 2: Operation stage of RNN.

The feature engineering stage aims to extract useful features from the original data for prediction tasks. This can be achieved by time domain analysis, frequency domain analysis, wavelet transform and other technologies. These characteristics can better characterize the internal laws and patterns of data. It presents a detailed account of the probability distribution associated with the transition between n states. In this context, P_{ij} denotes the probability of transitioning from state S_i to state S_i within a Markov chain, $0 \le P_{ij} \le 1$. In practical computations, the frequency of state transitions can be used as an approximation for the probability of such transitions. As an illustrative example, suppose we have sample data indicating that state S_i occurs m_i times, and there are m_{ij} instances of transitions from state S_i to state S_i. Under these circumstances:

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & & & \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{5}$$

It describes the probability distribution of the mutual transition of n states. Where P_{ij} is the probability of transition from state S_i to state S_i of Markov chain, and $0 \le P_{ij} \le 1$. In practical calculation, the frequency of state transition can be used as the probability of state transition. Assuming that according to the sample data, the quantity of times the state S_i appears is m_i, and the quantity of times the state S_i transitions to the state S_i is m_{ij}, at this time:

$$P_{ij} \approx \frac{m_{ij}}{m_j} \tag{6}$$

The RNN model is trained to learn the normal behaviour patterns of building performance parameters. This is achieved by training with historical data, and RNN can learn the time dependence and correlation between building performance parameters. In the training stage, the model will model the normal performance parameter data and learn how to distinguish the normal change range from the abnormal change. Once the model training is completed, real-time building performance parameter data can be input into the RNN model for anomaly detection. The RNN model will analyze the time series characteristics of the input data and compare it with the learned normal behaviour patterns. If there is an obvious deviation or abnormal change between the input data and the normal mode, the RNN model will trigger the anomaly detection mechanism. See Figure 3 for the detection process of abnormal parameters of building performance based on RNN.

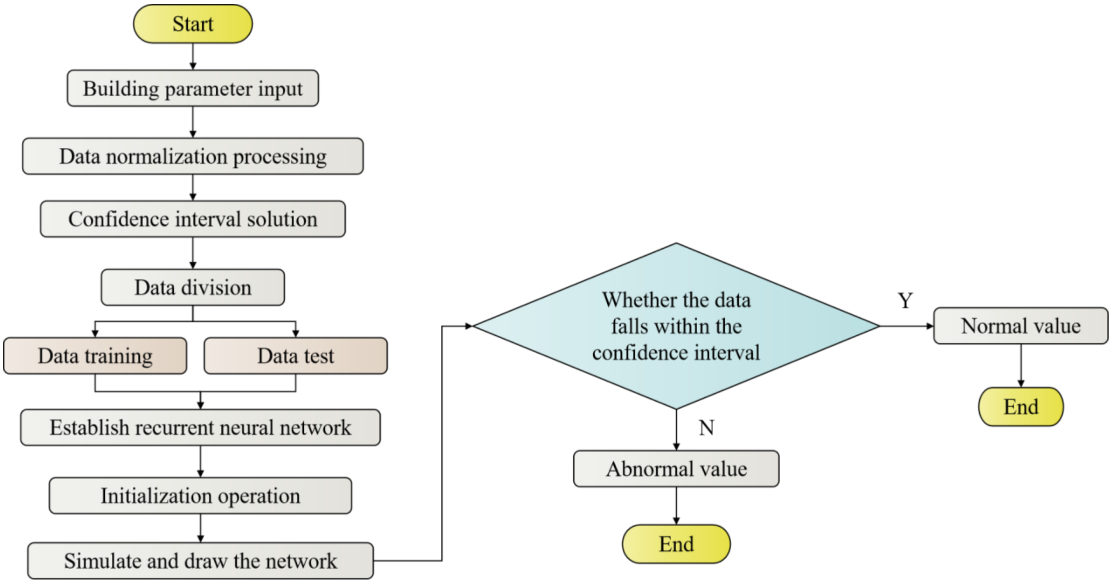

Figure 3: Detection of abnormal building parameters based on RNN.

Set the factor set U and the assessment grade set V for evaluating real estate projects:

$$U = \ u_1, u_2, \ldots, u_m \tag{7}$$

$$V = \ v_1, v_2, \ldots, v_m \tag{8}$$

Each factor U undergoes a fuzzy assessment process that relies on the grade indices outlined in the assessment set. This process yields the assessment matrix.

$$R = (r_{ij})_{n \times m} \tag{9}$$

Which r_{ij} indicates the degree of u_i 's membership v_i. Determine the importance index of each factor:

$$A = \ a_1, a_2, \ldots, a_m \qquad \sum_{i=1}^{n} a_i = 1 \tag{10}$$

Synthesis:

$$\bar{B} = AR = (\bar{b}_1, \bar{b}_2, \ldots, \bar{b}_m) \tag{11}$$

After normalization, the following results are obtained:

$$B = \ b_1, b_2, \ldots, b_m \tag{12}$$

So, the assessment grade of building performance can be determined.

After building a building performance prediction model based on RNN, a large quantity of time series data needs to be used for training. In the training stage, it is necessary to select. After the model training is completed, we need to carry out a series of assessment and optimization operations.

5 RESULT ANALYSIS AND DISCUSSION

5.1 Experimental Setup

The purpose of the experiment is to verify the advantages of building a performance prediction method based on RNN in response speed and prediction accuracy and compare it with the SVM method. Collect performance parameter data of real buildings, including temperature, humidity, energy consumption, etc. The collected data are cleaned, normalized and interval discretized to eliminate the influence of outliers and dimensions. Building performance prediction models based on RNN and SVM are constructed, respectively. RNN model adopts the structure of a circular neural network to capture the time dependence of building performance parameters. The SVM model adopts proper kernel function and parameter setting to adapt to nonlinear problems. The training set is used to train the two models, and the superparameter is adjusted through the verification set. In the training stage, the same batch of samples is randomly processed to enhance the generalization ability of the model.

5.2 Result Analysis

In order to avoid the loss of important information by excluding special data in data processing, this study adopts the method of interval discretization for quantitative data with large differences in data distribution interval. This processing method can effectively reduce the non-uniformity of data distribution and make the data easier to analyze and process.

As shown in Figure 4, the data after interval discretization shows obvious interval distribution characteristics. In each interval, the distribution of data is relatively concentrated, and the data differences between different intervals are more obvious. This processing method can not only reduce the non-uniformity of data distribution but also show the relationship and differences between different data more clearly.

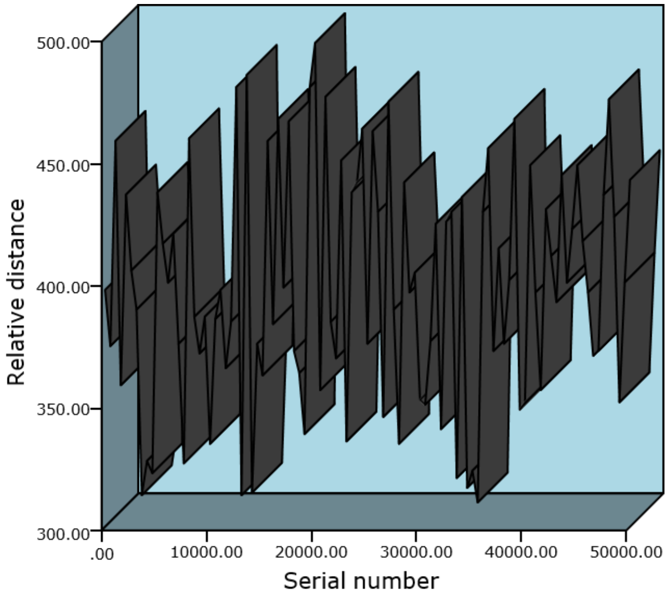

Figure 4: Data De-outlier processing.

The designed RNN is trained by using the data after interval discretization, and better network weights are obtained. By substituting these weights into RNN, a building performance prediction model is constructed. In order to verify the accuracy of the model, the output data of RNN are compared with the monitoring data of real buildings, and the results are shown in Figure 5.

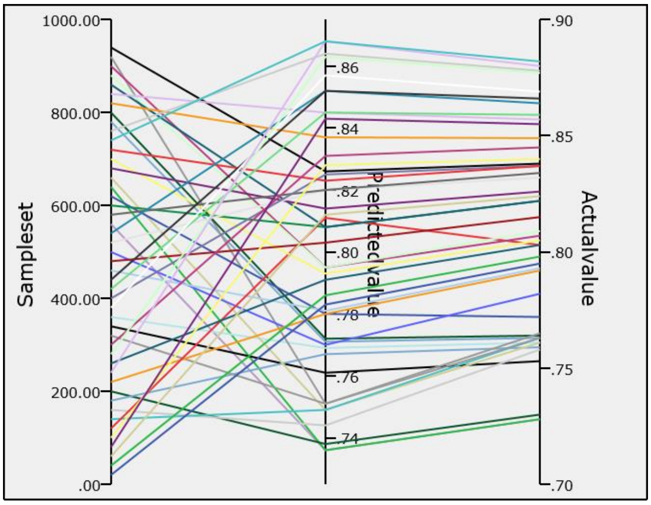

Figure 5: Machine learning results.

The output data of RNN are basically consistent with the real data, which shows that RNN has successfully learned the changing law of building performance, which shows that the model has high prediction accuracy. This is due to the adoption of an appropriate loss function and optimization algorithm and effective regularization in the training stage. Figure 6 shows the comparison of the errors of different building performance prediction models at different training stages.

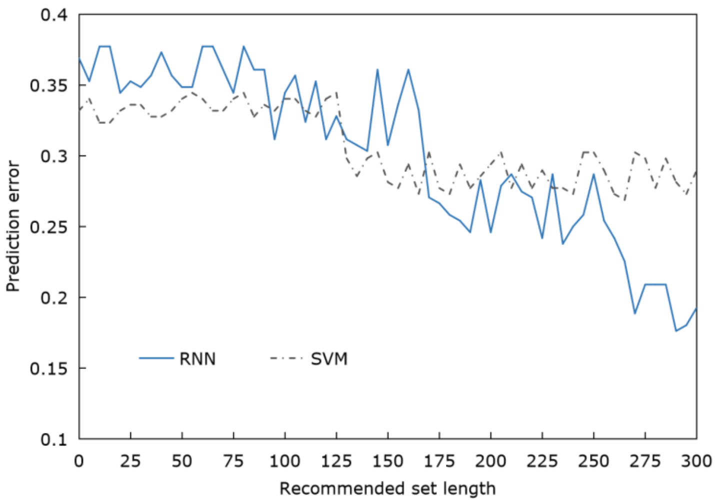

Figure 6: Comparison of prediction errors of algorithms.

Figure 6 shows the error comparison of different building performance prediction models in different training stages. With the increase of training iterations, the error of building a performance prediction model based on RNN gradually decreases. This shows that the RNN model gradually learns the inherent laws and patterns in the data during the training stage. In the process of training, the model constantly learns more information from the data and gradually optimizes its weight parameters. Through enough iterations, the model can reach a relatively stable performance level.

This change is due to the randomness of data introduced by random processing, which enables the model to learn information from different data subsets in each training, thus improving the generalization ability of the model. Performance prediction models, we tested them on the Matlab platform and adopted the running time as the assessment index of prediction efficiency. During the test, the calculation time of feature dimension reduction of different models is recorded, and the results are arranged in Table 1. Moreover, the accuracy of building performance prediction model of RNN and comparison method is compared, and the results are shown in Table 2.

Building type	*Training sample*		*Test sample*	
	SVM	*RNN*	*SVM*	*RNN*
Housing building	6.65	6.17	8.01	5.57
Commercial building	8.24	5.51	6.78	4.42
Industrial building	7.78	6.48	7.95	3.88
Public building	6.75	5.55	8.86	5.45

Table 1: Dimension reduction time of building performance prediction model.

Because of its unique cyclic structure, the RNN model needs more time to calculate. However, through the application of optimization algorithms and hardware acceleration technology, the calculation time of the RNN model has been significantly reduced. In contrast, other comparison methods have shorter calculation times, but they may not capture the time dependence and correlation between building performance parameters, so there are some limitations in prediction accuracy.

Building type	*Training sample*		*Test sample*	
	SVM	*RNN*	*SVM*	*RNN*
Housing building	88.52%	92.59%	83.44%	92.54%
Commercial building	81.38%	95.15%	86.27%	95.22%
Industrial building	86.35%	95.87%	87.89%	95.31%
Public building	87.53%	93.85%	81.55%	94.29%

Table 2: Correct rate of building performance prediction model.

The RNN model has obvious advantages in prediction accuracy. This is due to the fact that the RNN model can capture the time dependence and correlation between building performance parameters so as to predict future performance more accurately. Moreover, the comparison method is relatively low in prediction accuracy and cannot effectively deal with the complex relationship between building performance parameters.

The comparison of the response speed of the algorithm is shown in Figure 7. Compared with SVM, the method proposed in this article has obvious advantages in the early and late running, and the response speed has increased by 20.37%.

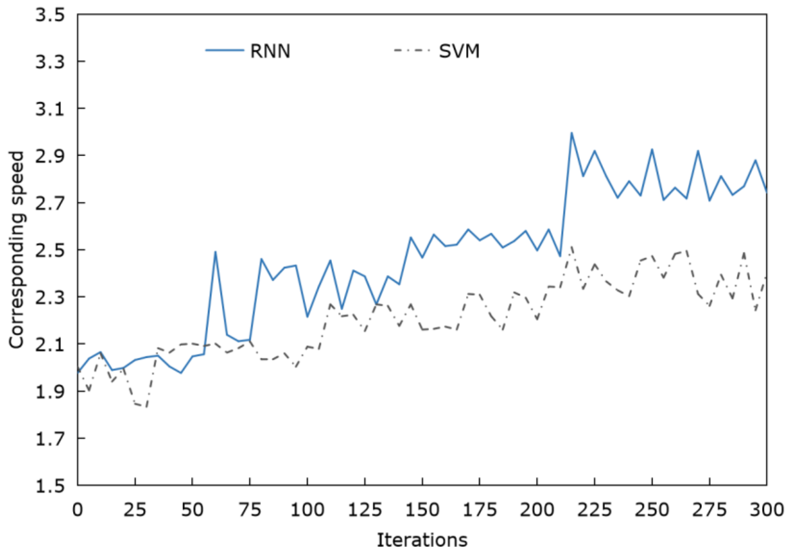

Figure 7: Comparison of response speed.

RNNs can respond faster by capturing past information and applying it to current prediction. In contrast, SVM is a method based on statistical learning theory, which may require more computing resources to deal with nonlinear problems. Because building performance parameters usually have complex time dependence and correlation, a model that can adapt to this data characteristic is needed. Because of its unique circular structure, RNN can capture these characteristics well.

However, SVM may need more kernel functions and parameter adjustments when processing this kind of data, which will increase the computational complexity and response time. In practical application, the running speed of the RNN model is further optimized by hardware acceleration technology. In practical application, this rapid response speed will help to find and solve the building performance problems in time, thus improving the safety of the building.

5.3 Result Discussion

The combination of AI and various industries has become a trend. In the field of building design, traditional CAD technology has brought great convenience to the industry. CAD technology allows designers to build two-dimensional and three-dimensional models on the computer, which provides unprecedented convenience for building design. As a deep learning technology, RNN is good at processing sequence data and capturing the time dependence in the data. Combining the two, RNN can be used to predict and optimize the performance of building design. The CAD system combined with RNN can provide real-time performance feedback for designers. Based on the prediction model of RNN, the automatic optimization algorithm can be developed, and the design parameters can be adjusted automatically to achieve the best performance. By directly integrating performance prediction and optimization into the design process, it can be ensured that performance factors are considered from the initial stage of design, thus realizing the deep integration of design and performance.

Through real-time feedback and automatic optimization, designers can find and solve potential performance problems early and reduce the cost of later modification and rework. RNN's predictive ability can help designers explore more design possibilities. By combining the prediction ability of RNN, we can predict and optimize the environmental impact of buildings more accurately and promote the growth of building design in a more sustainable direction.

6 CONCLUSION

In today's construction industry, it has become more and more important to accurately predict the performance of buildings. Traditional CAD software mainly focuses on geometric and aesthetic design, but it is relatively weak in predicting building performance. Therefore, the combination of RNN and CAD technology is expected to make up for this deficiency, thus improving the comprehensive performance of building design. In this article, RNN and CAD technology are combined and applied to building performance prediction. By directly extracting building information from CAD drawings and inputting it into the RNN model, the risk of data conversion and information loss is reduced, and the performance of prediction is improved. The advantages of RNN in dealing with building performance prediction: by capturing the time dependence and correlation between building performance parameters, RNN can achieve more accurate prediction. Through the application of random processing and hardware acceleration technology, the prediction efficiency and response speed are further improved.

The research results have application value for the building design industry. By combining CAD technology with RNN, a more efficient and sustainable building design method can be realized. With the continuous improvement of technology, this combination is expected to bring more breakthroughs to the building design industry in the future.

Nian Wu, https://orcid.org/0009-0007-1964-0306
Zhao Ye, https://orcid.org/0009-0001-7352-8776

REFERENCES

[1] Berseth, G.; Haworth, B.; Usman, M.; Schaumann, D.; Khayatkhoei, M.; Kapadia, M.; Faloutsos, P.: Interactive architectural design with diverse solution exploration, IEEE

Transactions on Visualization and Computer Graphics, 27(1), 2019, 111-124. https://doi.org/10.1109/TVCG.2019.2938961
[2] Denerel, S.-B.; Anil, G.: Computer aided drawing programs in interior architecture education, Amazonia Investiga, 10(39), 2021, 28-39. https://doi.org/10.34069/AI/2021.39.03.3
[3] Dounas, T.; Lombardi, D.; Jabi, W.: Framework for decentralised architectural design BIM and Blockchain integration, International Journal of Architectural Computing, 19(2), 2021, 157-173. https://doi.org/10.77/478077120963376
[4] Entezari, A.; Roohani, I.; Li, G.; Dunstan, C.-R.; Rognon, P.; Li, Q.; Zreiqat, H.: Architectural design of 3D printed scaffolds controls the volume and functionality of newly formed bone, Advanced Healthcare Materials, 8(1), 2019, 1801353. https://doi.org/10.1002/adhm.201801353
[5] Han, Y.-S.; Lee, J.; Lee, J.; Lee, W.; Lee, K.: 3D CAD data extraction and conversion for application of augmented/virtual reality to the construction of ships and offshore structures, International Journal of Computer Integrated Manufacturing, 32(7), 2019, 658-668. https://doi.org/10.1080/0951192X.2019.1599440
[6] Hu, S.; Meng, Q.; Xu, D.; Katib, I.; Aouad, M.: The spatial form of digital nonlinear landscape architecture design based on computer big data, Applied Mathematics and Nonlinear Sciences, 7(1), 2021, 783-790. https://doi.org/10.2478/amns.2021.1.00069
[7] Latif, M.; Ismail, M.-A.: Towards Multi-objective Optimization of automatic design space exploration for computer architecture through hyper-heuristic, Engineering, Technology and Applied Science Research, 9(3), 2019, 4292-4297. https://doi.org/10.48084/etasr.2738
[8] Roman, A.; Andrii, S.; Galyna, R.; Honcharenko, T.; Iurii, C.; Hanna, S.: Integration of data flows of the construction project life cycle to create a digital enterprise based on building information modeling, International Journal of Emerging Technology and Advanced Engineering, 12(1), 2022, 40-50. https://doi.org/10.46338/ijetae0122_05
[9] Safikhani, S.; Keller, S.; Schweiger, G.; Pirker, J.: Immersive virtual reality for extending the potential of building information modeling in architecture, engineering, and construction sector: Systematic review, International Journal of Digital Earth, 15(1), 2022, 503-526. https://doi.org/10.1080/17538947.2022.2038291
[10] Stojanovski, T.; Partanen, J.; Samuels, I.; Sanders, P.; Peters, C.: City information modelling (CIM) and digitizing urban design practices, Built Environment, 46(4), 2020, 637-646. https://doi.org/10.2148/benv.46.4.637
[11] Tytarenko, I.; Pavlenko, I.; Dreval, I.: 3D modeling of a virtual built environment using digital tools: kilburun fortress case study, Applied Sciences, 13(3), 2023, 1577. https://doi.org/10.3390/app13031577
[12] Wu, Y.; Shang, J.; Xue, F.: RegARD: symmetry-based coarse registration of smartphone's colorful point clouds with CAD drawings for low-cost digital twin buildings, Remote Sensing, 13(10), 2021, 1882. https://doi.org/10.3390/rs13101882
[13] Yi, H.: Visualized co-simulation of adaptive human behavior and dynamic building performance: an agent-based model (ABM) and artificial intelligence (AI) approach for smart architectural design, Sustainability, 12(16), 2020, 6672. https://doi.org/10.3390/su12166672
[14] Zhang, M.; Deng, X.: Color effect of landscape architecture design under computer aided collaborative design system, Computer-Aided Design and Applications, 19(S3), 2021, 13-22. https://doi.org/10.14733/cadaps.2022.S3.13-22
[15] Zhao, W.: An application of BIM technology in computer-aided building energy saving design, Computer-Aided Design and Applications, 18(S1), 2020, 133-143. https://doi.org/10.14733/cadaps.2021.S1.133-143