Fuzzy Logic-Based CAD Collaborative Design in Interior Design and Advertising Innovation

Weixin Lin[1], Xinyue Zhang[2], Zehe Yin[3] and Yongxin Liang[4]

[1,3,4] Hainan Vocational University of Science and Technology, Haikou, Hainan 571126, China,
[1]weixin.lin@dpu.ac.th, [3]zeheyin@gmail.com, [4]Laifeng991@outlook.com
[2]Hainan University, Haikou, Hainan 570228, China, xinyuecheung@hainanu.edu.cn

Corresponding author: Xinyue Zhang, xinyuecheung@hainanu.edu.cn

Abstract. CAD software is widely used in interior design and advertising innovation, but it has the problems that data cannot be shared, and information interactivity is weak, which makes it difficult to improve the communication efficiency between the designer and the user, enhance the user's sense of participation, and meet the user's personalized design requirements. Therefore, this paper constructs a CAD co-design (CAD Collaborative Design) model based on fuzzy logic and introduces the BP neural network and particle swarm algorithm for model improvement. Experimental results show that the improved BP neural network fuzzy logic model has better stability, convergence speed, and error rate and is able to carry out more detailed clustering of data according to user needs, providing more accurate data support for model application. In addition, in the application experiments, the CAD co-design model constructed based on fuzzy logic shows a shorter system corresponding time and lower packet loss rate than the control model in the application of advertising innovation. In the recommendation of indoor space layout methods, the model of this paper can complete a larger number of recommendations in a shorter time and improve user satisfaction.

Keywords: Fuzzy Logic; CAD Co-Design; Particle Swarm; Interior Design; Advertising Innovation
DOI: https://doi.org/10.14733/cadaps.2024.S26.115-128

1 INTRODUCTION

The maturity and development of CAD technology for interior design and advertising innovation design provide strong technical support, not only providing two-dimensional plane planning and design but also showing three-dimensional effects to provide users with more realistic visual effects, so CAD in the design field in a wide range of applications. In the field of interior design, advertising innovation is the key to attracting customers and driving business growth. With the rise of indoor location services, indoor maps, an important foundation of location services, have attracted widespread attention. The three-dimensional form of indoor maps has become the preferred form of representation for indoor maps due to its realistic immersive experience and better user experience. At present, 3D indoor maps are mainly produced based on user-uploaded building post-processing or offline collection+post-processing using some hardware. Due to the low level of automation in these two mapping modes, they are struggling in large-scale mapping, resulting in an increasingly prominent contradiction between mapping efficiency and demand. Agarwal et al. [1] improved the efficiency of 3D indoor mapping by creating semi-automatic or automated technical systems, which has become one of the key methods to solve the field of indoor location services.

In the era of digital design, advertising design is gradually breaking away from the traditional one-way design model and developing towards a more user-centred and interactive direction. CAD collaborative design based on fuzzy logic, as an advanced design method, provides new possibilities for product advertising design, especially in achieving user empowerment, demonstrating enormous potential. Arrighi and Mougenot [2] explore how to achieve user empowerment in product advertising design through this interactive reality tool. In advertising design, user empowerment means placing users at the core of the design, fully respecting and reflecting their opinions and needs. This not only requires designers to have in-depth communication with users but also requires design tools to support this bidirectional and dynamic interaction process. In the past, interior design and advertising innovation design is based on a linear model, in this design mode, the design to the designer as the main body of the design, the user is difficult to integrate into the interior space design planning, subjective expression is relatively weak. Binocular vision technology can achieve precise perception and understanding of three-dimensional space by simulating the visual system of human eyes. As an important tool for interior design, CAD models provide designers with rich spatial information and design inspiration. Ben and Cengiz [3] explored the research on interior design and advertising visual orientation guidance based on CAD models under binocular vision. The interior design based on CAD models provides strong data support for the application of binocular vision technology. As a digital representation of interior design, CAD models contain rich spatial information and design elements. By combining CAD models with binocular vision systems, designers can preview and adjust design schemes in real time in real scenes, achieving rapid verification and optimization of design effects. This not only improves design efficiency but also reduces design costs, providing more possibilities for the practice of interior design. At the same time, the design team size is relatively small, the design experience of individual designers has limitations and there is a certain difference between the changing user aesthetic style, it is difficult to maintain a high level of design in the design style and design quality.

Borgue et al. [4] explored how to integrate additive manufacturing components into interior design based on fuzzy models and promote sustainable development in this field through advertising innovation. A fuzzy model is a mathematical tool that can handle uncertainty and fuzziness problems, and it can be used to describe and analyze the behaviour and characteristics of complex systems. In the design of additive manufacturing components, traditional design methods often find it difficult to meet the requirements due to the complexity and uncertainty of material properties, structural strength, and usage environment. The design method based on fuzzy models can establish corresponding fuzzy rules and membership functions based on experience and experimental data to predict and optimize the performance of components. At the same time, different designers have different evaluation standards for design quality due to the influence of professional quality, design style and other factors, coupled with limited sharing of information, narrow communication, and lack of professionalism and effectiveness in the evaluation of the design program review mechanism. Digital urban landscape planning and advertising design have gradually become an important component of urban development. As one of the core technologies in digital city construction, spatial information technology provides strong support for urban landscape planning and advertising design. Deng et al. [5] explored the application of spatial information technology in digital urban landscape planning and advertising design. Spatial information technology provides precise data support and visual expression for digital urban landscape planning. In terms of advertising design, spatial information technology also plays an important role. Through spatial positioning technology, advertising designers can accurately determine the position and orientation of billboards, ensuring that the advertising content is coordinated with the urban landscape. In addition, using spatial information technology, designers can also analyze dynamic information such as urban pedestrian and vehicle flows, in order to develop more targeted advertising strategies and improve the dissemination effect of advertisements.

Therefore, in the face of the user's changing needs is difficult to reflect innovative design concepts and elements in the design, but also unable to recommend the design information and design methods needed for the user, the user is able to participate in the design process is also relatively few opportunities. In such a state, it is very difficult for users to fully understand the design content and design information in a short period, and often due to serious information overload caused by the existence of large errors in the design concepts of both sides, resulting in the need for designers to repeat a large amount of groundwork, increasing the time and economic costs, and affecting the efficiency and quality of the design. The field of interior design is undergoing unprecedented changes. Designers are increasingly relying on advanced technology and algorithms to assist them in completing complex design tasks. Among them, CAD interactive evolutionary computation based on fuzzy logic has become an important method, providing new possibilities for interior design. Huang et al. [6] explored the design categories in interior design experiments based on this method. The CAD interactive evolutionary computation indoor design experiment based on fuzzy logic covers various design categories. Each type of space has its unique needs and characteristics, therefore requiring different design strategies and methods. Secondly, classification based on design style is also an important dimension. Based on fuzzy sets, the algorithm will generate a series of initial design schemes. These plans may include different elements such as layout, materials, colours, etc.

In view of the above problems, some scholars have proposed the concept of collaborative design, that is, through CAD software and network communication technology to realize the purpose of multi-participants in the design. Collaborative design can be both the designer and the user to do people collaborative design, can also be more than one designer to complete the same design. Through CAD software co-design can improve the information interaction between designers and users, between designers and designers, reduce repetitive groundwork, and improve communication efficiency and design efficiency through real-time interaction. The computer-aided design method for indoor landscape planning and advertising parameterization models, with its unique advantages and characteristics, is gradually becoming an important tool for designers to pursue innovation and efficiency. Jia [7] discussed the application and advantages of computer-aided design methods for indoor landscape planning and advertising parameterization models. In advertising design, parameterized models also play an important role. Advertising designers can use parameterized models to quickly generate advertising design plans that meet the requirements based on factors such as the theme, target audience, and promotional effect of the advertisement. By adjusting parameters, designers can flexibly change the visual elements of advertisements such as layout, colour, and font, achieving personalization and differentiation of advertisements. At the same time, users can put forward their own opinions and suggestions through CAD software to increase the level of design participation. In addition to achieving information and experience sharing, designers can also rationally optimize the design process in all aspects through collaborative management, reducing unnecessary economic costs and time costs, which is conducive to improving the coherence of the entire design process and improving the level of design intelligence. However, the current multi-person collaborative design platform also has problems such as the lack of richness of data resources, functional modules to be improved, poor accuracy of relevant information recommendations, and long response time for information interaction. Therefore, this paper introduces fuzzy logic in the BP neural network to construct a CAD collaborative design and intelligent information recommendation model, which can extract and categorize the data features of designers' and users' needs and recommend the corresponding data information according to the results, which improves the accuracy of recommended information and reduces the response time under the circumstance of ensuring the integrity of data.

2 CURRENT STATUS

In recent years, embedded collaborative filtering recommendation systems have gradually become a research hotspot, and their application in housing advertising innovation has also received increasing attention. Jun et al. [8] used embedding techniques to map users and items to the same vector space. Then, the similarity between the user and the item is calculated in order to recommend a method for recommending items with higher similarity to the user. The system converts users and listings into vector representations through embedding techniques. Khan et al. [9] addressed the shortcomings of existing CAD drawing analysis methods in terms of robustness, birefringence, and quick reference efficiency. It designed the algorithm of merging adjacent and capping parallel wall lines to preprocess the drawings, improving the fault tolerance of the search loop algorithm on the drawings. Then, a new drawing parsing strategy was proposed around the creation and use of custom data structures - semantic polygons. Based on this, several algorithms have been designed to improve the extraction efficiency, accuracy, and richness of conventional building components such as doors and windows. And achieved the extraction of detailed modelling parameters for complex building components, such as stairs and elevators. Enable it to support parametric modeling during the 3D reconstruction phase. Finally, the improved search ring algorithm is used to extract the boundary of the functional area. And expand the method of identifying functional area types beyond semantic annotation to obtain spatial pattern information for the entire floor.

Lin et al. [10] proposed a non-edge-oriented vector indoor road network generation algorithm to address the shortcomings of existing vector indoor road network generation algorithms that have edge tendencies (i.e., paths close to or located on wall lines). The road network data generated by this algorithm has no edge tendency compared to traditional visual graph methods. Due to the clear and simple road network, the storage space occupies less space. In addition, to make the results more universal, it also designed a method to convert indoor road network results into a universal road network storage format - an undirected weighted graph. For the reproduction of 3D indoor scenes and the integrated storage of 2/3D indoor map data, it has designed a parametric modelling algorithm for building components and a complete scene assembly method for mainstream GIS platforms using the ArcEngine interface. And designed a 2D and 3D integrated data storage model for Geodatabase. As the core organizational unit of a city, the traditional way of representing buildings in two-dimensional planes can no longer meet people's needs for integrated management and analysis of indoor and outdoor buildings. Many scholars have studied the standards for building 3D models in the fields of BIM and GIS and proposed an integrated representation method for indoor and outdoor buildings based on BIM+GIS. Orlova [11] studied the building spatial information model of BIM+GIS, starting from the open standard IFC (Industry Foundation Classes) in the BIM industry and the open standard City GML in the geographic information industry. It explores the construction of geometric, semantic, and topological attributes of building spatial information models starting from the planar CAD data of buildings. Finally, through an example of an intelligent management system in a park, the application concept of the building spatial information model is verified.

Compared with other methods, the indoor map generation method based on CAD building floor plans also has the following advantages. It is a method that can simultaneously extract spatial, attribute, and topological data, which is contained in the building plan and can be automatically extracted using appropriate strategies and algorithms. Meanwhile, due to the availability of spatial, attribute, and topological relationship data, indoor path data can be automatically generated through algorithms based on this foundation. This method extracts and generates data entirely through software, with a high level of automation and efficiency in data production; there is no need to purchase expensive equipment for field collection, which can save hardware, labour, and time costs. Through algorithm design, this method can automatically derive additional vector indoor road network data based on drawing data, providing road network data support for indoor navigation, which cannot be achieved by other hardware methods [12]. Song and Jia [13] studied the simplification algorithm of CAD data based on traditional planar CAD data for designing architectural spatial information models. Secondly, construct a family model for the special building components of the research object. Finally, implement the construction of indoor and outdoor models of buildings on

Revit. Abstract the space of the model based on the characteristics of the research object, and implement the spatial inclusion relationship of the building through coding. And implement the construction of spatial connectivity relationships on ArcGIS. A three-dimensional model of architectural spatial information was designed from the perspective of BIM+GIS for the application scenarios of architectural models. Using the Unity3D engine, a park intelligent management system was developed based on the constructed 3D model. Through six major functions including virtual roaming, environmental simulation, asset management, measurement analysis, construction simulation, and emergency response plans. In fact, it realizes the integration of indoor and outdoor roaming and browsing of building models, spatial measurement of indoor and outdoor objects, and querying of building components, verifying the design of the model from the application level.

Visual communication technology and art in the field of interior design and advertising media are undergoing unprecedented changes. The development of computer-aided interaction technology has provided designers with richer and more efficient tools and platforms. Integrating visual communication technology with art more closely, bringing new creativity and experiences to interior design and advertising media. Wang [14] constructed a 3D model to simulate real scenes, achieving rapid iteration and optimization of design schemes. By utilizing technologies such as virtual reality and augmented reality, advertising designers can create more vivid and realistic advertising scenes to attract the audience's attention. At the same time, through interactive technology, advertising designers can also interact with the audience, allowing them to participate in the advertisement, improving the participation and dissemination effect of the advertisement.

The application of GIS from outdoor to indoor has become an inevitable trend, and research and application of indoor location services have emerged. In the context of the increasingly prominent contradiction between the production efficiency and demand of indoor map data, Zhang and Deng [15] developed an efficient method for generating three-dimensional indoor maps based on CAD architectural floor plans. In terms of identifying building components, it proposes the idea of combining floor spatial patterns to identify internal building components in rooms, breaking the traditional fixed pattern of relying solely on geometric and semantic features to identify building components. This makes it possible to extract detailed parameters of complex building components such as stairs and elevators based on floor plans. Extract sufficient parameters to restore the indoor 3D scene as realistically as possible. In the recognition of floor spatial patterns, extending the method of identifying functional area types beyond semantic guidance can significantly capture the recognition ability of room types. Zhao [16] proposed a new drawing parsing strategy around the creation and use of custom data structures - semantic polygons. It designs a series of algorithms to extract parameters from seven common types of building components (floors, walls, balcony railings, doors, windows, stairs, elevators). Simultaneously extracted floor spatial pattern information (spatial, attribute, and topological information of functional areas). And export the drawing analysis results into a universal cross-platform format XML file so that it can be converted to different formats of indoor map storage models. In terms of collaborative design, how to better promote communication and cooperation between different disciplines and fields, as well as how to share and utilize knowledge and resources more effectively, are also challenges that need to be addressed.

3 CAD CO-DESIGN MODEL CONSTRUCTION BASED ON FUZZY LOGIC

3.1 Neural Network-Based Fuzzy Logic Arithmetic Modeling

Fuzzy logic is capable of modelling the reasoning ability possessed by humans and is often used in the fields of control of nonlinear systems, expert systems, and recognition models. Neural networks have good learning performance and parallel processing ability, as well as high fault tolerance and generalization ability. The essence of the complementary combination of the two is a fuzzy logic system, where neural networks can effectively avoid the dependence of fuzzy rules on subjectivity, and fuzzy logic can overcome the black-box nonlinear mapping problem that exists in neural networks. A neural network-based fuzzy logic model replaces the fuzzy control design with the training and learning of a neural network through the learning performance and mapping performance of the neural network equivalent to the fuzzy function module in the system to realize the self-learning performance and self-adaptive performance of the system.

A fuzzy logic system heavy fuzzy set is a set that does not have a clear boundary, let the domain of the argument denoted as M , where white shouting of any $x, x \in M$ has the corresponding affiliation function, notated as $\mu A(x)$, then it is a fuzzy set on the domain M , as shown in Eq:

$$\underset{\sim}{A} = (\mu_{\underset{\sim}{A}}(x) \big| x) \tag{1}$$

Among others, $\forall x \in M, \mu_{\underset{\sim}{A}}(x) \in [0,1]$.

If a fixed element is selected in the argument domain M , denoted as $x_0 \in M$, and the variable set of motion boundaries it contains is denoted as A^*, then $x_0 \in A^*$ or $x_0 \notin A^*$, whose affiliation expression is shown in (2):

$$\mu(x_0) = \lim_{i \to \infty} \frac{n}{i} \tag{2}$$

where the degree of affiliation is denoted as $\mu(x_0)$ and the number of $x_0 \in A^*$ is denoted as n .

The BP neural network algorithm, also widely known as the error backpropagation algorithm, is a training algorithm based on a multilayer feedforward network that adjusts the network weights by backpropagating the errors to optimize the network output. The core structure of the algorithm consists of three or more neural network layers, each playing a different role. The input layer is responsible for receiving incoming data or signals from the outside world. This input data is initially processed and passed on to the next layer. The hidden layer is the most crucial part of the BP neural network. The hidden layer can have one or more layers, and each layer contains multiple neuron nodes. These nodes are not directly connected to each other but are connected to the nodes in the next layer through weights. The main role of the hidden layer is to extract and transform features from the input data so that the output layer can better process it. The output layer is responsible for transforming the feature information passed from the implicit layer into the final output result. The result of the output layer is compared with the expected result and the error is calculated. This error is then propagated backward following the original path, and the error is reduced by adjusting the weights between the layers. This process is iterated until the output of the network meets the predetermined accuracy requirements.

In the BP neural network algorithm, the initialization of the weight coefficients is a key step, that affects the training speed and final performance of the network. Let the weight coefficients of each layer be denoted as W_{nm} and set as small and non-zero random numbers, the input samples are denoted as $X = (X_1, X_2, ..., X_i)$ the output samples are denoted as $Y = (Y_1, Y_2, ..., Y_i)$ and the corresponding output of the neuron with the sequence number of n in the sequence number of denoted as X_n^l then it is as shown in Eqs. (3) and (4):

$$U_n^l = \sum_{m=1}^{i+1} W_{nm} X_m^{l-1}, X_{m+1}^{l-1} = 1, W_{n,i+1} = -\theta \tag{3}$$

$$X_n^l = f(U_n^l) \tag{4}$$

The learning error for each layer is denoted as d_n^l when $l = j$ exists for the output layer as shown in equation (5):

$$d_n^j = X_n^j (1 - X_n^j)(X_n^j - Y_n) \tag{5}$$

Combining the correction coefficients and the threshold values gives the values as shown in Eqs. (6) and (7):

$$\Delta W_{nm} = -\eta \cdot d_n^l \cdot X_m^{l-1} U_n^l = \sum_{m=1} W_{nm} X_m^{l-1} \tag{6}$$

$$W_{nm}(t+1) = W_{nm}(t) - \eta \cdot d_n^l \cdot X_m^{l-1} \tag{7}$$

where the correction factor is denoted as W_{nm} and the threshold value is denoted as θ .

A single neuron can conveniently realize simple affiliation functions in fuzzy logic, while the desired characteristics of the affiliation function can be easily achieved by simply setting the excitation function. Various shapes and properties of the affiliation functions can be accurately modelled by appropriately configuring the excitation function of the neuron to meet different application requirements. The excitation function in this paper is shown in Equation (8):

$$f(net) = \exp(\frac{-(net - z)^2}{\sigma^2} \tag{8}$$

Where the total input of the neuron is denoted as net, the mean centre of the affiliation function is denoted as z , and the mean squared deviation of the width of the affiliation function is denoted as σ. A schematic diagram of the neural network-based fuzzy logic model is shown in Figure 1.

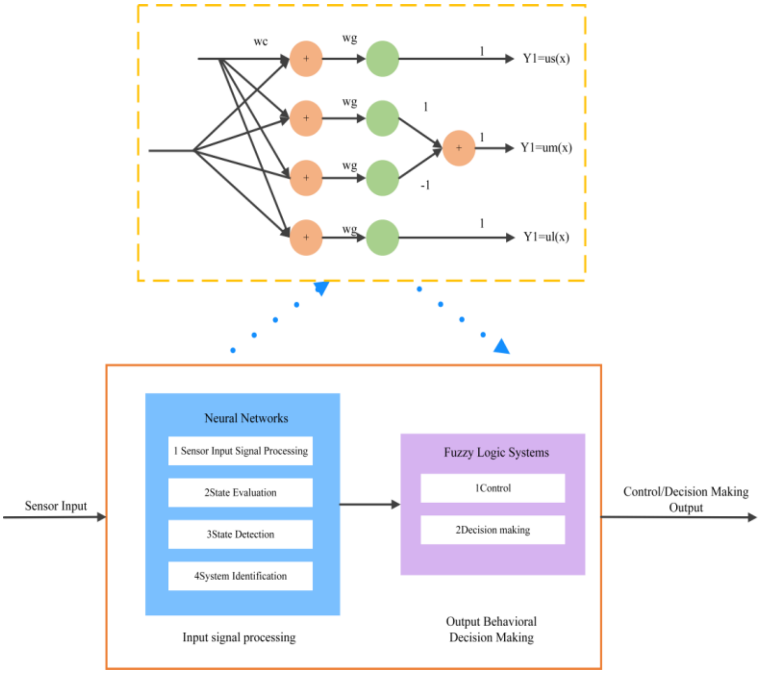

Figure 1: Schematic diagram of fuzzy logic model based on neural network.

From the figure, it can be seen that the output of the node labelled with + represents the sum of the inputs, and the excitation function of the other nodes is chosen as a Sigmoid function, then it is shown in Equation (9):

$$y_1 = \mu_s(x) = \frac{1}{\{1 + \exp[-w_g(x + w_c)]\}} \tag{9}$$

where the weights are denoted as w_g, w_c, which play a decisive role in the centre position and width of the Sigmoid function, respectively.

The realization of fuzzy logic operations through neural networks also needs to be set to consider its training process requires microscopic neuron excitation function to reach the goal, which can be achieved by substituting the original min operation, as shown in Equation (10):

$$(\alpha \wedge \beta) = Soft\min = \frac{\alpha e^{-h\alpha} + \beta e^{-h\beta}}{e^{-\alpha} + e^{-\beta}} \tag{10}$$

3.2 Fuzzy Logic-Based Information Base Data Retrieval Model

The PSO algorithm, or particle swarm optimization algorithm, is an evolutionary computational technique based on the study of bird feeding behaviour in flocks, which is rooted in the theory of group intelligence and aims to achieve global optimization. The algorithm is not only able to efficiently perform optimization operations for multidimensional spatial functions and dynamic objectives but is also highly valued for its fast convergence speed and excellent robustness. These advantages give the PSO algorithm significant application value in solving complex optimization problems.BP neural network exists local optimal results in the process of information search so that the interior design or advertisement creative information provided to the user has a large error, so this paper optimizes the fuzzy logic model based on the neural network by POS algorithm to improve its performance of retrieval of information database data. If you want to use global search in the POS algorithm in the spatial search process is limited, you can increase the inertia weight to get a linear decreasing particle swarm algorithm; the larger the value of the weight of its global search ability, the contrary, the local search performance is higher, the convergence is higher. However, the actual search has a strong nonlinearity and high complexity, and there is a discrepancy between the linear decreasing particle swarm algorithm and the actual search optimization results citation This paper proposes a dynamic particle swarm algorithm to improve the neural network-based fuzzy logic model.

Let the inertia weight factor be denoted as w , the evolutionary speed factor of the particle be denoted as h , and the aggregation factor be denoted as g , then the three expressions are shown in Eqs. (11)-(13):

$$w = f(h, s) \tag{11}$$

$$h = \frac{\min(Fgbest_{T-1}, Fgbest_T)}{\max(Fgbest_{T-1}, Fgbest_T)} \tag{12}$$

$$g = \frac{\min(Fgbest_T, \bar{F}_T)}{\max(Fgbest_{T-1}, \bar{F}_T)} \tag{13}$$

Where $0 < h \leq 1$, the mean of all particles' current adaptation values is denoted as $\bar{F}_T$, as shown in Equation (14):

$$\bar{F}_T = \frac{1}{N * \sum_{n=1}^{N} X_T[n]} \tag{14}$$

Where the particle iteration sequence number of is nT sits at the position denoted as $X_T[n]$ and the particle swarm size number is noted as N .

When the particle swarm exhibits a faster rate of evolution, the algorithm is able to continuously explore a wide search space, enabling the particles to perform optimization in a large range. However, as the particle swarm evolution slows down, the search space can be narrowed by decreasing the value of ω, allowing the particle swarm to perform fine searches in a small range, thus approaching the optimal solution faster. In addition, when the distribution of particles is more dispersed, the particle swarm is less likely to fall into a local optimal solution, which helps to maintain the algorithm's global optimization search capability. However, as the degree of aggregation of the particle swarm increases, the risk of the algorithm falling into a local optimum will also increase accordingly. At this time, the global search ability of the particle swarm can be enhanced by increasing the search space to avoid premature convergence to local optimal solutions. It can be seen that the relationship between w and the evolutionary speed factor exhibits a negative correlation, and the relationship with the aggregation degree factor exhibits a negative correlation, as shown in Equation (15):

$$w = w_{ini} - h * w_h + g * w_g \tag{15}$$

Where, the initial value of w is denoted as w_{ini}, and the scale factors of the evolutionary speed factor and aggregation factor are w_h and w_g respectively. The flow chart of the particle swarm optimization BP neural network is shown in Figure 2.

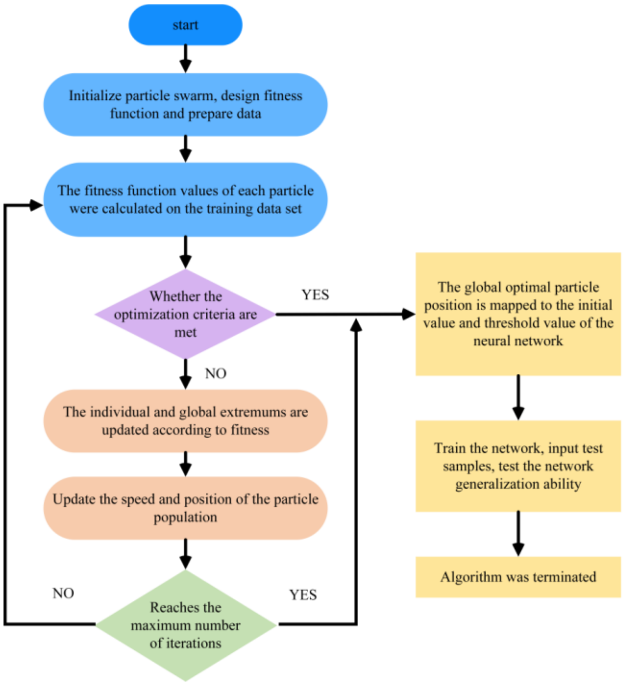

Figure 2: Particle swarm optimization BP neural network flowchart.

4 EXPERIMENTS ON THE INNOVATIVE APPLICATION OF FUZZY LOGIC-BASED CAD CO-DESIGN MODEL IN INTERIOR DESIGN AND ADVERTISING

In order to verify the performance of a fuzzy logic-based CAD co-design model in interior design and advertising innovation, this paper first verifies the performance of a fuzzy logic model based on an improved neural network through a comparison experiment. The models compared in this experiment contain three kinds of fuzzy logic models, linear decreasing particle swarm algorithm (LDPSO) and improved BP neural network fuzzy logic model. The convergence speed and global optimal solution iteration comparison results of the three models are shown in Figure 3. In the (a) figure, it can be seen that the fuzzy logic model and LDPSO have the same starting adaptation value, and the gap between the two increases gradually with the increase in the number of iterations. The adaptation value of the improved neural network logic algorithm model starts relatively low and the final value is the most efficient among the three models. That is, the slowest convergence among the three algorithmic models is the fuzzy logic model and the fastest convergence is the improved neural network logic, algorithmic model. This shows that the improved algorithm solves the problem that the original BP neural network is prone to fall into the local optimum, and the optimal solution obtained by it is the best among the three models in terms of minimal value optimization. In Figure 3(b), it can be seen that the training convergence speed of the LDPSO fuzzy neural network is relatively slower than that of the improved algorithm model, and the improved global optimal solution performs better. This shows that the fuzzy logic-based CAD co-design model can avoid the drawbacks of the other two algorithms in the application and has the best global search performance.

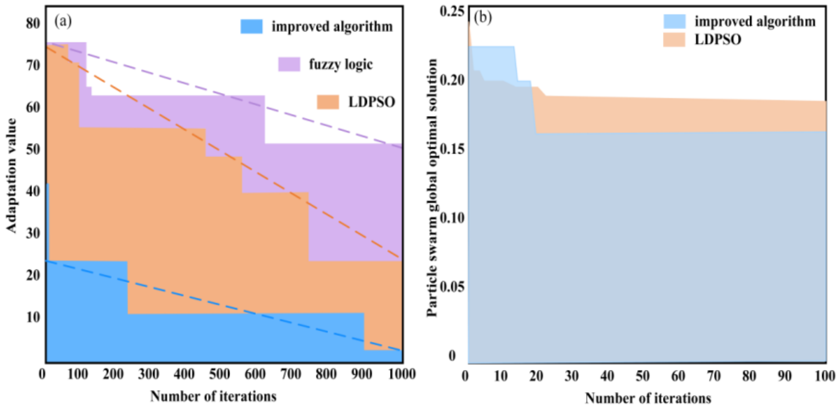

Figure 3: Convergence speed and global optimal solution iteration comparison results of the three algorithmic models.

In order to further verify the application performance of the improved algorithm model, this paper compares its error with that of the LDPSO fuzzy neural network, and the results are shown in Figure 4. From the data in the figure, it can be seen that the error of the improved fuzzy logic model of the neural network is more stable than the LDPSO error performance, and the magnitude of the change is relatively small.LDPSO in the later stage due to the complexity of the actual application of the situation is higher and there is a larger error situation, the stability of the relatively poor. In addition, combining the results in Figure 3(b), it can be seen that when the convergence speed of the improved model algorithm reaches a more optimal state, its error can also reach a more optimal state, so the optimal solution obtained is better than the optimal solution of LDPSO.

The classification results of the improved neural network fuzzy logic model for user search information and demand information are shown in Figure 5. The two models classify the same sequence ensemble, and the different coloured regions indicate different clustering areas. From the data results, it can be seen that in the case of the same sequence ensemble and the same number of samples, the results of the improved model categorization are finer than the clustering results of the LDPSO model, and the number of samples contained in each category is closest to the actual situation. This shows that the improved algorithmic model can improve the information classification performance of the fuzzy logic-based CAD co-design model, which can provide targeted information data according to the needs and requirements of users.

The above experimental results show that the introduction of the improved neural network in the CAD collaborative design model based on fuzzy logic can improve the convergence speed of the model, reduce the error, obtain better global search results, carry out more detailed clustering of different data information, more in line with the actual needs, and provide effective and accurate data for the model to be applied in the interior design and advertisement innovation in a shorter time.

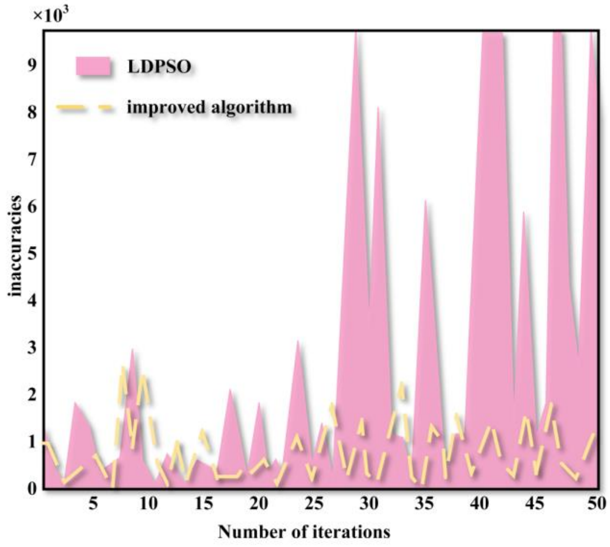

Figure 4: Comparison results of fuzzy neural network error between improved neural network fuzzy model and LDPSO model.

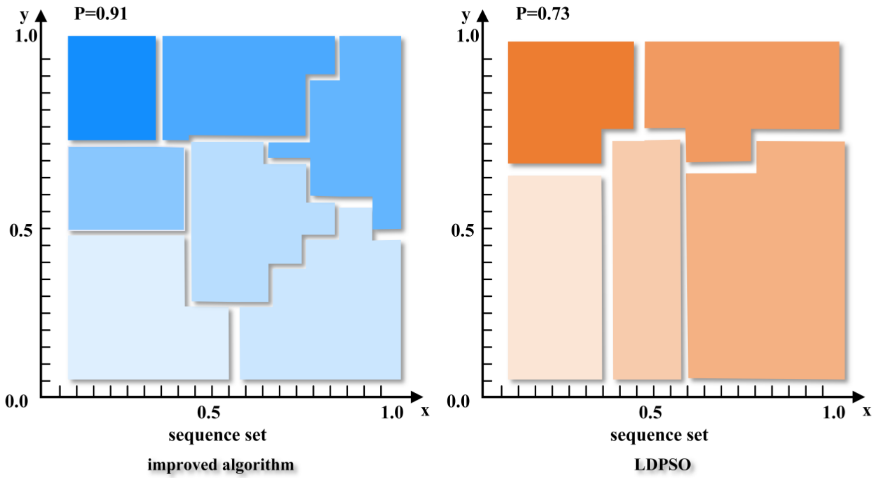

Figure 5: Comparison of classification results of two algorithmic models for data information.

Information support. In order to verify the application performance of the CAD co-design model based on fuzzy logic, this paper conducts a comparative experiment on the performance of advertising innovation information recommendation. The experiment contains the model of this paper and the collaborative recommendation model, as shown in Figure 6. As can be seen from the data in the figure, the comparison experiment compares the system latency and packet loss rate of the two models. Among them, the system latency curve trend of the two models is consistent, i.e., they are both relatively low in the early stage and start to increase more substantially in the middle and late stages. However, the model system in this paper starts to show latency improvement only after the data reaches 600, while the collaborative recommendation model starts to show significant improvement when the data reaches about 450. In terms of packet loss rate, the curves of the two are also significantly improved in the middle and late stages, and the model in this paper starts to show the phenomenon of packet loss rate improvement when the data reaches 550 and gradually stabilizes in a short period. Collaborative recommendation model packet loss rate in the data to reach 400 or so appears to improve the phenomenon, and in the late stage before the gradual stabilization of the region. This shows that the data continuity and accuracy of the model in this paper is better, the ability to deal with data is more, and in the case of increasing data, in a short period, it shows good stability.

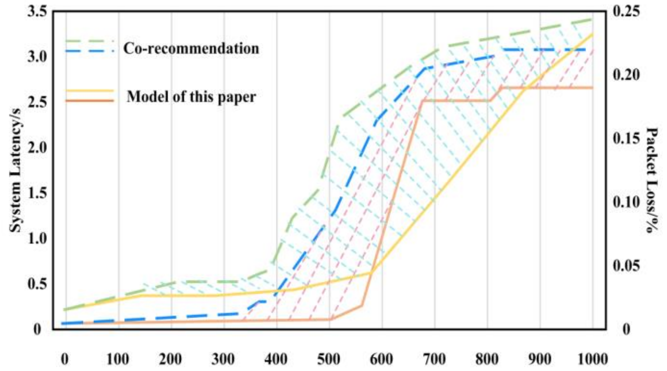

Figure 6: Results of two models in advertising innovative information recommendation delay and packet loss rate.

As shown in Figure 7 the fuzzy logic-based CAD co-design model and collaborative recommendation algorithm according to the user demand recommended indoor space layout method time comparison results. Dismissal from the figure oh can be seen, with the increase in the number of recommendations, the model of the user demand classification and data processing workload enhancement, the recommendation time is not short of enhancement. However, the recommendation time of the algorithmic model in this paper is 60% to 72% shorter than the recommendation time of the collaborative recommendation model, which is more efficient. Meanwhile, according to the user satisfaction level, it can be seen that users recognize the performance of this paper's model more.

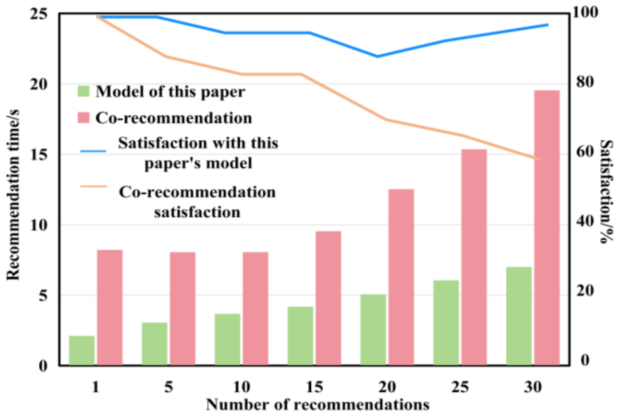

Figure 7: Time comparison results of indoor space layout methods recommended by the two models according to user requirements.

5 CONCLUSIONS

Traditional CAD-based interior design and advertising innovations are designer-centered, and it is difficult for users to incorporate and present their own views in the design process. However, as users' emphasis on personalization and their own style increases, it is difficult for traditional design models to meet users' needs. To address such problems, multi-person collaborative design can solve the communication problems and information interaction problems between designers and users, and designers can obtain user opinion information in time, and can also recommend appropriate data information according to user needs. Therefore, this paper constructs a CAD collaborative model based on fuzzy logic and optimizes and improves the model by combining the BP neural network and particle swarm algorithm. The experimental results show that the improved BP neural network fuzzy logic model shows better stability and convergence speed compared with other models, and has better global search performance. At the same time, its error rate of user information processing is lower, and the clustering of data information is more detailed and more in line with the actual situation, which can improve the performance of the CAD collaborative model constructed based on fuzzy logic in the application of interior design and advertising innovation. In addition, through the application of comparative experimental results, in the case of the same data, the model in this paper in the advertising innovation application of the system delay time is shorter, and the later enhancement can quickly stabilize, and the packet loss rate is also lower. In the indoor space layout method recommendation time, this paper's model, in the case of the same number of recommendations, can result in a substantial reduction in the recommendation time at the same time to improve the user's satisfaction with the model.

Weixin Lin, https://orcid.org/0009-0007-5168-8203
Xinyue Zhang, https://orcid.org/0009-0008-4100-5541
Zehe Yin, https://orcid.org/0009-0008-5567-7189
Yongxin Liang, https://orcid.org/0009-0007-2557-2442

REFERENCES

[1] Agarwal, D.; Robinson, T.-T.; Armstrong, C.-G.; Kapellos, C.: Enhancing CAD-based shape optimisation by automatically updating the CAD model’s parameterization, Structural and Multidisciplinary Optimization, 5(9), 2019, 1639-1654. https://doi.org/10.1007/s00158-018-2152-7
[2] Arrighi, P.-A.; Mougenot, C.: Towards user empowerment in product design: a mixed reality tool for interactive virtual prototyping, Journal of Intelligent Manufacturing, 30(2), 2019, 743-754. https://doi.org/10.1007/s10845-016-1276-0
[3] Ben, Y.; Cengiz, K.: Research on visual orientation guidance of industrial robot based on cad model under binocular vision, Computer-Aided Design and Applications, 19(S2), 2022, 52-63. https://doi.org/10.14733/cadaps.2022.S2.52-63
[4] Borgue, O.; Panarotto, M.; Isaksson, O.: Fuzzy model-based design for testing and qualification of additive manufacturing components, Design Science, 8(1), 2022, 1-26. https://doi.org/10.1017/dsj.2022.6
[5] Deng, Y.; Xie, L.; Xing, C.; Cai, L.: Digital city landscape planning and design based on spatial information technology, Neural Computing and Applications, 34(12), 2022, 9429-9440. https://doi.org/10.1007/s00521-021-06377-w
[6] Huang, W.; Su, X.; Wu, M.; Yang, L.: Category, process, and recommendation of design in an interactive evolutionary computation interior design experiment: a data-driven study, AI EDAM, 34(2), 2020, 233-247. https://doi.org/10.1017/S0890060420000050
[7] Jia, J.: Computer-aided design method of parametric model for landscape planning, Computer-Aided Design and Applications, 19(S3), 2022, 55-64. https://doi.org/10.14733/cadaps.2022.S3.55-64

[8] Jun, H.-J.; Kim, J.-H.; Rhee, D.-Y.; Chang, S.-W.: "SeoulHouse2Vec": An embedding-based collaborative filtering housing recommender system for analyzing housing preference, Sustainability, 12(17), 2020, 6964. https://doi.org/10.3390/su12176964
[9] Khan, M.-T.-H.; Demoly, F.; Kim, K.-Y.: Constructing assembly design model capable of capturing and sharing semantic dynamic motion information in heterogeneous CAD systems, The International Journal of Advanced Manufacturing Technology, 111(3), 2020, 945-961. https://doi.org/10.1007/s00170-020-06046-7
[10] Lin, Z.; Cui, C.; Wu, G.: Dynamic modeling and torque feedforward based optimal fuzzy PD control of a high-speed parallel manipulator, Journal of Robotics and Control (JRC), 2(6), 2021, 527-538. https://doi.org/10.18196/jrc.26133
[11] Orlova, E.-V.: Design technology and AI-based decision-making model for digital twin engineering, Future Internet, 14(9), 2022, 248. https://doi.org/10.3390/fi14090248
[12] Pane, Y.; Arbo, M.-H.; Aertbeliën, E.; Decré, W.: A system architecture for cad-based robotic assembly with sensor-based skills, IEEE Transactions on Automation Science and Engineering, 17(3), 2020, 1237-1249. https://doi.org/10.1109/TASE.2020.2980628
[13] Song, P.; Jia, J.: Indoor scene generation based on case-based reasoning and collaborative filtering, Journal of System Simulation, 31(2), 2019, 263-274. https://doi.org/10.16182/j.issn1004731x.joss.18-VR0699
[14] Wang, R.: Computer-aided interaction of visual communication technology and art in new media scenes, Computer-Aided Design and Applications, 19(S3), 2021, 75-84. https://doi.org/10.14733/cadaps.2022.S3.75-84
[15] 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
[16] Zhao, X.: Application of 3D CAD in landscape architecture design and optimization of hierarchical details, Computer-Aided Design and Applications, 18(S1), 2020, 120-132. https://doi.org/10.14733/cadaps.2021.S1.120-132