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Research Article

Intelligent Construction Optimization Control of Construction Project Schedule Based on the Fuzzy Logic Neural Network Algorithm

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At present, the field of construction engineering is limited by various situations, such as complex construction environments and many uncertain factors. Therefore, on the basis of the engineering network diagram, this paper proposes a construction project schedule management method based on the fuzzy logic neural network algorithm. By building a neural network, a large amount of historical data is input, and computers are allowed to calculate the key routes, thus predicting the construction period, and a construction project in a city is taken as an example for simulation experiments. The traditional construction period management scheme expects a construction period of 55 days. The planned construction period optimized by the project management technology integrating fuzzy logic neural network algorithm is 55 days, which is 2 days less than the traditional construction project schedule management technology and will not cause construction period delay. The simulation results show that this algorithm is more accurate and more efficient in calculating the key lines when dealing with large-scale projects, which can help the construction unit to quickly find the optimal strategy and effectively reduce the construction delay and capital loss caused by uncertainty factors.

1. Introduction

Construction project schedule control refers to the preparation of the project schedule according to the overall schedule objectives and the principle of resource optimization formulated at the beginning of the project, and the construction is carried out in accordance with the schedule, according to the work content, procedures, time consumed, and handover relationship of each stage of the construction project. Then, in the process of project construction, it is checked whether the actual progress of the project is consistent with the planned progress. If there is any deviation, it is a process of analyzing the deviation, taking control measures, modifying the plan and continuing to implement it according to the new plan, and so on until the final completion of the project. The most important indicator of project schedule control is the project duration. However, due to the complex construction environment, there are many uncertain factors, which often occur in all stages and posts of construction, and will have a far-reaching impact on the project schedule. Therefore, the on-site control personnel need to analyze those factors that may affect the progress before the project starts, estimate the possible consequences of these factors, and prepare a reasonable and feasible schedule on this basis so that the project can proceed smoothly according to the plan.

Many scholars have conducted a lot of research on project schedule control. Based on the study of many well-known project schedule management cases, this paper analyzes the mutual influence between project objectives, safety, quality and cost, and schedule management and expounds on the characteristics and applicable environment of some basic methods (such as the Gantt chart method, flow construction plan, plan review technology, S-curve method, critical path method, and so on) widely used in on-site schedule management. This method solves the problem that the traditional schedule management method does not consider resource constraints and has been praised by many researchers [2]; Tao and Tam integrate the three objectives of the project: quality, progress, and cost into a system and explore ways to maximize comprehensive benefits [3]; Bhaskaran studied the operability of applying plan review technology to expressway project schedule management [4]; Chen et al. used the latest Group Support System software to track and control the progress [5]. In the research of network planning technology, most of the research focuses on resource-constrained project scheduling problem (RCPSP). Stinson proposed an integer programming model for RCPSP under renewable resource constraints. Since then, many researchers regard this model as a standard model and turn their focus to the solution of this model [6]. For this model, the current solution is mainly achieved through a mathematical programming algorithm. Sood et al. elaborated and solved the problem in detail by using dynamic programming and linear programming, and the solution result is very ideal [7]; Patrick et al. proposed a linear programming model based on primal-dual relationships to solve the RCPSP model, which also achieved good results [8]. In the study of activity time, the critical chain technology uses a fixed value, while the plan review technology determines the duration of the project according to three different types of time: the most optimistic time, the most likely time, and the most pessimistic time of the controller for the project progress, which is also known as the three-point estimation method of time. At first, the three-point estimation method used empirical formulas, but with the deepening of research, many scholars proposed many new methods based on empirical formulas. For example, Newbold summarized seven-time estimation methods and studied their respective variances and expectations of different methods on the premise that the processing time obeyed the triangular distribution [9].

A neural network, also known as an artificial neural network, is an active network composed of simple calculation and processing units (i.e., neurons) as nodes and uses a certain network topology. The artificial neural network can fully approach any complex nonlinear relationship and can learn and adapt to unknown or uncertain systems. All its quantitative or qualitative information is stored in each neuron in the network with equipotential distribution, which has strong robustness and fault tolerance. The parallel distributed processing method is adopted, which makes it possible to carry out a large number of operations quickly [10].

The research of neural networks has a history of more than half a century since the 1940s. In 1943, American psychologist McCulloch cooperated with mathematician Pistt to study the description of objective events in formal neural networks with logical-mathematical tools, put forward the excitation and inhibition neuron model, and initiated theoretical research on neural networks. Psychologist Hbeb proposed the modification rule of neuron connection strength in 1949, and their research is still the basis of many neural network models. In 1957, Rosneblatt proposed the perceptron model, which started almost at the same time as AI, but it did not achieve the great success of AI for more than 30 years and experienced a long depression in the middle [11]. After the 1970s, the research on neural networks was at a low tide. Until the 1980s, practical algorithms for artificial neural networks were obtained, and turing digital computers encountered physical insurmountable limits in the artificial intelligence of analog audio-visual systems, people renewed their interest in artificial neural networks, leading to the revival of neural networks, and the upsurge of neural networks was raised again. At present, the research on neural network theory mainly focuses on network algorithms, performance, and the use of neurophysiological cognitive science to study human thinking and intelligent mechanisms [12]. Application research mainly focuses on the software simulation and hardware implementation of neural networks and the application of neural networks in various fields, such as pattern recognition, signal processing, knowledge engineering, expert systems, optimization combination, robot control, and others [13–15]. The research results include the BP algorithm of multilayer network, the proposal of the network model, and the introduction of the energy function, neural network model of competition and cooperation, Boltzmann and self-organizing feature mapping network model, and so on [16]. Neural networks and schedule management are both hot areas of current research. However, various uncertain factors on the construction site make it difficult for the construction to proceed smoothly according to the original plan, and it is very easy to produce deviations. Therefore, if you want to really have reasonable and efficient progress control, you must give different solutions according to different environments and different factors [17]. The application of the fuzzy earned value method and fuzzy control to the analysis of schedule deviation and case-based reasoning to the formulation of deviation measures is exactly what is needed for schedule control at present. At the same time, the model in this paper can be widely applied to different research fields. Different projects in different fields only need to establish a case base and measure base corresponding to their field, and the model can be used equally.

The main innovations and contributions of this paper include the following points:

(1) Combing the methods and theories of traditional progress control, this paper gives the definition and connotation of project progress management based on the logical neural network algorithm, which lays a foundation for the application of fuzzy control in the field of construction engineering. Through the fuzzy earned value method, the actual data of the construction site is transformed into the input variables of the fuzzy controller, which is convenient for subsequent fuzzy control reasoning.

(2) The process and strategy of scheduled fuzzy control are described. The progress fuzzy controller is constructed, and the strength of control measures is deduced by using fuzzy reasoning technology.

2. Problems Existing in the Progress Management of Existing Construction Projects

It is particularly important for construction enterprises to improve their construction level and efficiency so as to enhance their competitiveness in the industry. From the perspective of the overall development trend of project management, the progress control of the project almost represents the whole project management in the initial development stage of project management [18]. Generally, in the whole life cycle of a project, the construction stage of the project is the most important stage, and whether the progress control of the project construction stage is effective or not is directly related to the success or failure of the project. For construction enterprises, project progress control is a key method to ensure the success of the project [19]. The main reasons are first of all, the construction of a project lasts for a long time, the construction environment is complex, and accidents often occur, resulting in schedule delays; at the same time, the construction process requires a lot of collaboration, and the handover between processes is complex [20]. Usually, a small error will cause a delay in progress. Finally, the final result of the project is not only to complete the construction project on time but also to consider various factors such as quality, cost, and so on [21]. Therefore, project managers need to comprehensively consider various factors to maximize the overall benefits of the project, which will also have an impact on the progress control part.

Based on the analysis of the history, definition, and process of traditional progress control, we can conclude that the current system of construction project progress control is still very imperfect, as shown in the following points:

(1) The mode of schedule control has not yet formed a systematic system and lacks modern management means. Although the traditional progress control method has been implemented for a long time, the truly systematic progress control is still in its infancy, and the corresponding systems and specifications are also quite imperfect [22]. At the same time, the amount of information obtained by the project parties is different, which will also lead to information asymmetry, which will affect the understanding of the project participants. Moreover, an engineering project generally contains a large amount of information. It is time-consuming, laborious, and impractical to rely solely on the project site managers to collect and manage this huge amount of information [23].

(2) The traditional schedule control lacks an accurate control model, and human subjective factors are significant. In essence, progress control means that the construction enterprise controls the construction period of the whole project. However, due to the one-time nature, liquidity, and complexity of the project, as well as various uncertainties that may be encountered in the construction process, the progress will be affected. Therefore, it is difficult to establish a fine and accurate model to control the progress of the construction, and it is more difficult to express it with a mathematical model, which can only be controlled by the subjective experience of the on-site management personnel. This will cause the personal ability of the controller to be directly linked to the control results, which will introduce potential risks to the benefits of the project [24].

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3. Problem Statement and Research Ideas

How to deal with the current situation of nonintelligent progress control in construction enterprises is an important problem to be solved by construction enterprises. After consulting and learning from a large number of theories and literature studies, this paper proposes to integrate the fuzzy logic neural network algorithm technology into the optimization of project schedule control. The fuzzy control model of project progress is a model that integrates the analysis of the causes of progress deviation, the calculation of progress deviation, and the proposal of specific control measures. It includes the following three intelligent control methods: the fuzzy earned value method, fuzzy control, and case-based reasoning, which solves the problem that the influencing factors of schedule control are complex and the calculation model cannot be accurately established. During the construction process of the project, the model continuously collects the corresponding information, uses the quantitative fuzzy earned value method to analyze the progress deviation, and then uses the rules of fuzzy control to solve the control quantity of the project progress [26–28]. This model is to continuously collect corresponding information during the construction of the project and determine the key technical nodes affecting the construction period in combination with the key chain identification technology. The key chain identification technology process is shown in

Figure 1. The quantitative fuzzy earned value method is used to analyze the progress deviation, and then the fuzzy control rules are used to solve the control amount of the project progress. Finally, the final progress deviation control measures are given with the help of case-based reasoning technology. It helps the on-site schedule control personnel to make decisions, thus reducing the possibility of making mistakes due to the inexperience of the on-site schedule control personnel, and provides a new idea for the current construction project schedule control field.

4. Optimization of Construction Project Schedule Management Based on the Fuzzy Logic Neural Network Algorithm

4.1. Logical Neural Network Algorithm. Classical reinforcement learning is a tabular method, which is prone to dimension disaster when dealing with high-dimensional data features. Inspired by deep learning, the combination of the two forms of neural network learning and fuzzy logic neural network algorithms are particularly widely used in deep reinforcement learning. See Figure 2 for the structure of the neural network.

The fuzzy logic neural network algorithm is a classical deep reinforcement learning algorithm based on value function. It combines convolutional neural networks (CNN) with the Q-learning algorithm, takes advantage of CNN's strong representation ability of images, regards video frame data as the state input network in reinforcement learning, and then outputs a discrete action value function from the network, and the agent selects the corresponding action according to the action value function. The convolutional neural network (CNN) and the Q-learning algorithm are shown in Figure 3.

The reason why the fuzzy deep neural network algorithm can better combine deep learning and reinforcement learning is that it introduces three core technologies, namely, objective function, objective network, and experience playback mechanism. The training process is shown in Figure 4.

(1) Objective function: we use convolutional neural network combined with full link as the approximator of action value function to achieve an end-to-end effect. The input is an image, and the output is a finite action value function.

(2) Target network: in order to make the performance of the fuzzy depth neural network algorithm more stable, two network models including CNN are used for learning. First, the network model $Q\ (s,\ a,\ w)$ replaces the predictive Q network to evaluate the value corresponding to the current state action; the second is to use the network model $Q\ (s,\ a,\ w')$ instead of the target Q network to calculate the target value. In this way, the fuzzy depth neural network loss function $L\ (w)$ under the dual network architecture can be obtained as follows:

$$L(w) = E_{\pi_w}\left[\left(r + \gamma \max_{a'} Q(s', a', w') - Q(s, a, w)\right)^2\right]. \quad (1)$$

In this formula, w represents the network parameters in the loss function, and E represents the mathematical expectation. $r + \gamma \max_{a'} Q(s', a', w')$ represents the target value of Q network optimization, where w'represents the parameters of the target network. Depth Q network updates network parameters based on gradient rules formula loss function can be obtained by deriving the following weight:

$$\nabla_w L(w) = E_{\pi_w}\left[\left(r + \gamma \max_{a'} Q(s', a', w') - Q\ (s, a, w)\right)\nabla Q(s, a, w)\right]. \quad (2)$$

In formula (2), ∇ represents gradient calculation. The structure and initial parameters of the dual network are the same, that is, $w_0 = w'$. After several rounds of iteration, there is $w' = w$. Therefore, the logical neural network algorithm is introduced into the target network, and the target Q value remains unchanged for a period of time, which reduces the possibility of loss value oscillation and divergence during training, fully ensures the training time, and improves the stability of the algorithm.

Experience playback mechanism: the logical neural network algorithm introduces the experience playback mechanism to store the experience migration samples obtained from the interaction between the agent and the environment at each time in the experience pool. After a number of steps, the batch size samples are randomly taken from the experience pool and input into the neural network as discrete data, and then the small batch random semigradient descent method is used to update the network parameters.

4.2. Fuzzy Depth Neural Network Algorithm Q Value Update Method for Project Schedule Management. The key design point of the fuzzy depth neural network model is to update the Q value. According to the characteristics of the project, in order to make the network more stable, this paper designs two neural networks with the same structure but different parameters and updates the actual value and estimated value of Q, respectively, to realize the convergence of the value function. The update process is shown in Figure 5.

At the same time, the fuzzy depth neural network algorithm uses a memory bank to learn from the previous experiences. Each time it is updated, the previous experience will be randomly selected for learning. For this project, the

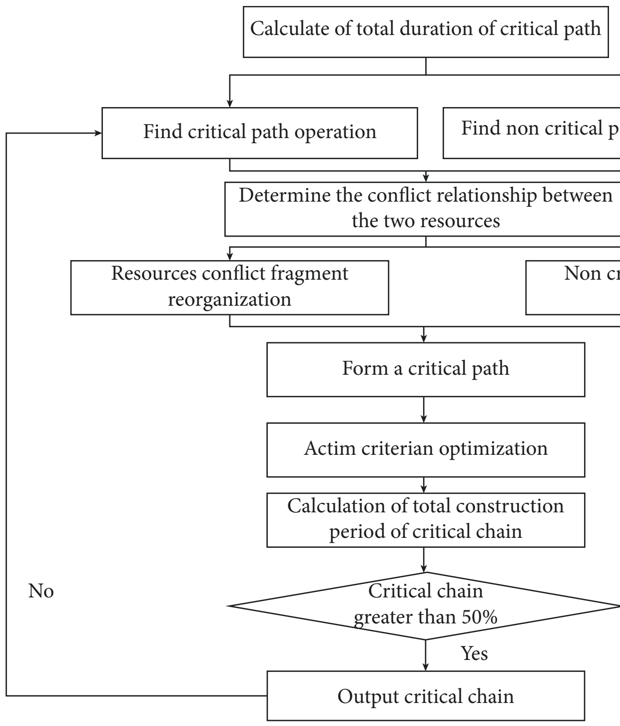

Figure 1: Key chain identification technology process.

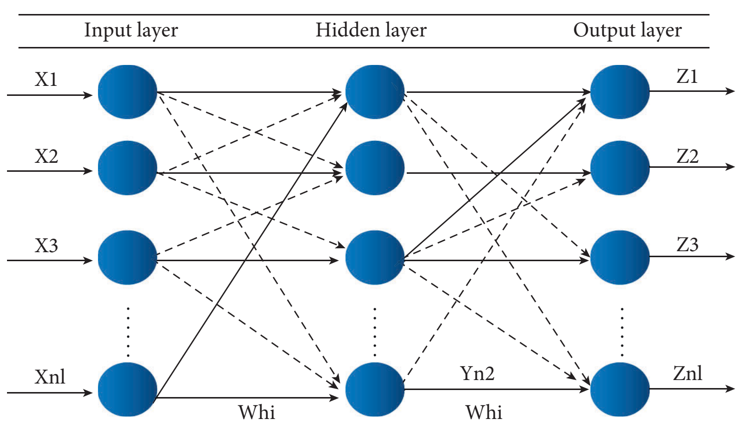

Figure 2: Structure diagram of the neural network.

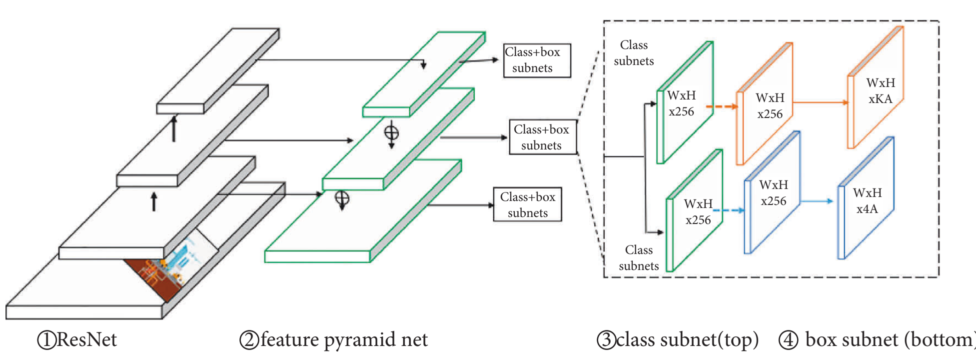

Figure 3: Convolutional neural network CNN and Q-learning algorithm.

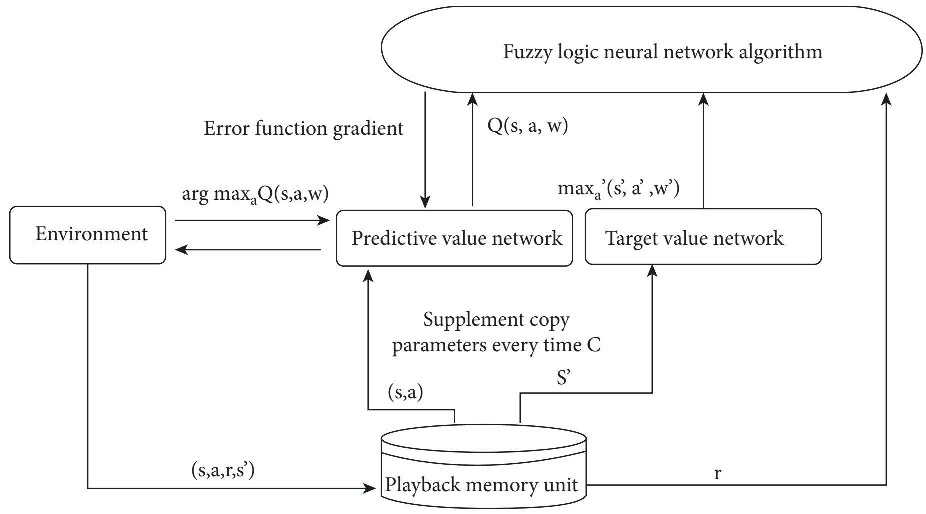

Figure 4: Training process of the logical neural network algorithm.

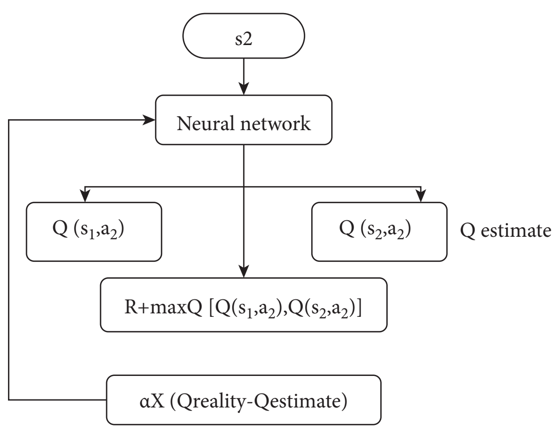

Figure 5: Updating process of the fuzzy depth neural network.

target network is updated with two networks with the same structure but different parameters, which makes the efficiency higher and more stable. In neural network training, instability or training difficulties may occur. To solve this problem, the fuzzy depth neural network adopts a target network and experience playback pool to improve. The loss function used is

$$L(w) = (R + \gamma \max (Q(s\prime, a\prime, w) - Q(s, a, w)))^2. \quad (3)$$

The fuzzy depth neural network algorithm uses two neural networks with the same structure but different parameters. The neural network that predicts the estimated value of Q uses the latest parameters, while the actual value of Q also uses the latest parameters of the neural network, which can make the training process more stable.

4.3. Selection of State and Action. The setting of the state is very important to the influence of the experiment. According to the characteristics of the project, this paper abstracts the events of the project's construction as stated. The data selected in this paper has a total of 21 events, that is, there are 21 states, and the state space is set as S. si indicates the i-th state ($i = 1, 2, 3, \ldots, 21$). The transition between states is represented as an action, A represents action space, and ai indicates the i-th action ($i = 1, 2, 3, \ldots, 21$). There are 21 actions as well as states.

In reinforcement learning, agents gain rewards by constantly interacting with the environment how to find an optimal strategy when interacting with the environment without losing too many rewards in the process of trial and error; we need a good method to balance. Exploration is the agents' continuous trial and error to collect more information and expand the memory bank. It will not bring great rewards in the short term but a long-term return. The use is to make the best choice under the current state according to the current memory bank, obtain immediate rewards, and focus on short-term returns, but this will lead to damage to long-term interests. So, this article combines ε-greedy ($0 < \varepsilon < 1$) select, where, $\varepsilon = 0.9$, that is, the best choice can be made in 90% of cases and random selection in 10% of cases. Through this setting, not only short-term interests but also long-term interests can be guaranteed.

4.4. Setting of Reward Function. The ultimate goal of neural network learning is to maximize the reward obtained. In this experiment, the time taken for the last event to reach the next event is set as the reward value, G is the reward value function, and R represents the immediate reward obtained by the agent after executing action a from the current state S to the next state S. With the immediate reward, we can get the reward value obtained by the last event to the next event in the project as critical path. The reward function is calculated as follows:

$$G = \lambda G_{t+1} + R_{t+1}. \quad (4)$$

In this formula, the total return is equal to the discount reward of the next state plus the immediate reward, where λ is the discount factor. This formula also indicates that the

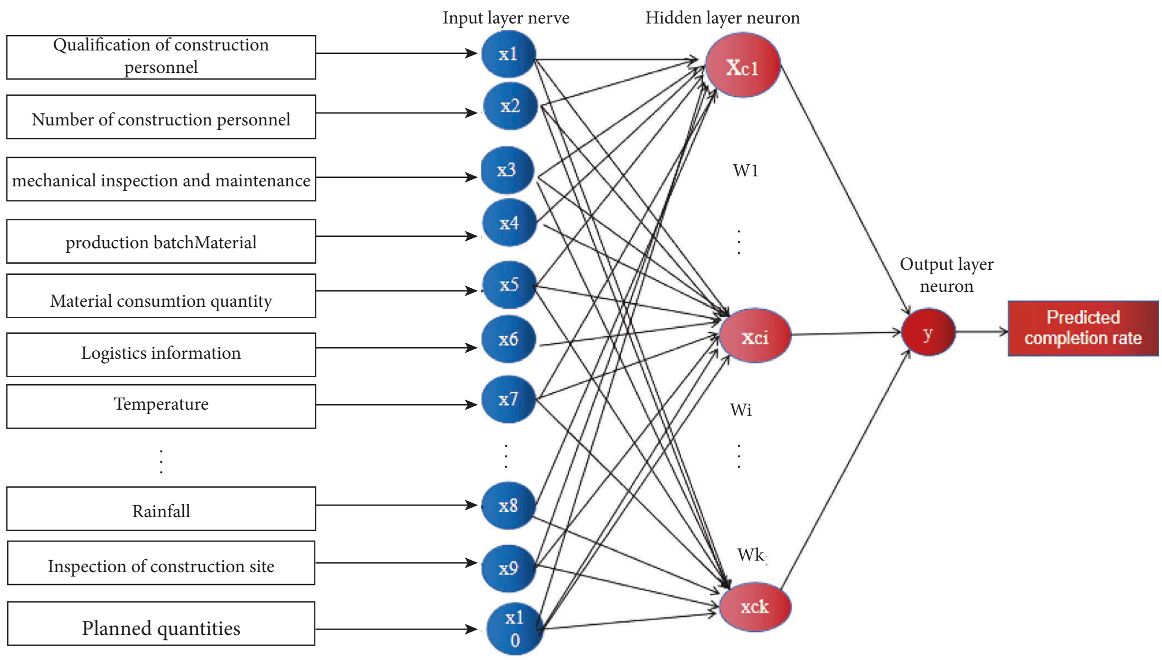

Figure 6: Fuzzy logic neural network work progress prediction model.

greater the reward value obtained from the previous event to the next event in the project, the greater the probability of choosing the optimal path.

The prediction model of engineering project construction progress and completion rate designed in this paper mainly uses the RBF neural network to imitate the information processing ability of biological neural cells. The basic idea of the RBF neural network is to use the radial basis as the hidden units to constitute the hidden layer space, directly mapping the input vector to the hidden layer space, without being connected by the weights. The central point of the RBF neural network is determined first, thus determining the mapping relationship between the systems. The implicit layer space is linearly mapped to the output space, and the output of the neural network is a linear weighted sum of the hidden cell output, while the weight is the tunable parameters in the neural network. This paper uses the fuzzy logic neuron network function, which randomly selects the center point setting method of the RBF's network, and directly selects the sample points as the network center points. During the training process, according to the target error set by the model, new hidden layer nodes are continuously added to the neural network structure, and the center point of the basis function is adjusted until the expected error requirements are met. See Figure 6 for the construction progress prediction model of the fuzzy logic neuron network.

5. Empirical Application of Construction Project Schedule Management Based on the Fuzzy Logic Neural Network Algorithm

5.1. Introduction to Experimental Cases. A construction project in a city needs to be constructed. The project requires a tight completion time, involves a wide range of events, the work is closely intersected, and the technical requirements are high. All departments attach great importance to it and require the construction personnel to quickly find the critical path to complete it. According to historical data and previous project progress, data collection and sorting are carried out, as shown in Table 1.

Table 1: List of logical relationships among various works of the project.

Work	Immediate work	Duration
A	—	2
B	A	4
C	A	3
D	B	2
E	B, C	6
F	B, C	1
G	D	4
H	D, E	3
I	D, E, F	2
J	G, H	6
K	I	1
L	J, K	2
M	L	4
N	L, M	3
O	N	3
P	M, N	2
Q	O	5
R	P	1
S	Q	4
T	Q, R	6
U	S	6
V	S, T	2
W	U, T	4
X	W	3

It can be seen from Table 1 of the project with a total of 21 events that according to the logical relationship between various works, we can get a project activity network diagram, as shown in Figure 7. Using the traditional critical chain method to find the critical path needs a lot of artificial calculation, and they not only have to spend a lot of manpower material resources but also there may be an error. Therefore, this paper uses the fuzzy deep neural network algorithm in deep reinforcement learning to train and find out the key routes so as to predict the construction cycle.

5.2. Simulation Experiment Process. It can be seen from Table 1 that there are 21 events in this project, and the rewards obtained by the transfer of work can be obtained from the logical relationship between each event, forming the reward matrix. This experiment is implemented using the TensorFlow platform, programmed with the Python language, and trained with the fuzzy depth neural network algorithm. First, events are abstracted as states, and the transfer between events is abstracted as actions, which are input into the neural network at the same time, and then processed with the convolutional neural network. The number of convolution cores in two layers is 21 and 42, respectively, and the size of the convolution core is $3 * 3$. In the training process, set the discount factor of Q-learning $\lambda = 1$. The number of iterations $N = 1000$, the size of the experience pool $D = 1000$, the number of samples extracted each time batch $= 50$, and set the learning rate of neural network $\alpha = 1$. With the setting of these parameters, after inputting the data into the neural network, the neural network will judge and finally output the action value. The Q reward matrix is as follows:

$$Q = \begin{bmatrix}
0 & 52 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 50 & 49 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 46 & 43 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 46 & 35 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 40 & 0 & 41 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 34 & 40 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 34 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 37 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 32 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 31 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 29 & 28 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 25 & 24 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 22 & 16 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 15 & 17 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 15 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 13 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 9 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 7 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 3 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}. \tag{5}$$

5.3. Simulation Project Progress Results. According to the training results of the fuzzy depth neural network algorithm, we can get the value of each work moving to another work, as shown in Figure 8.

According to the simulation project results, when the Q matrix converges, the agent can learn the key route of the project management progress. It can be seen from this that when the state is 1, the optimal transfer mode is 2, and the corresponding value is 52. When the state is 2, the transferable states are 3 and 4, and the corresponding values are 50 and 49, respectively. When the value is larger, the selection is 50, that is, the transfer mode is 3. By analogy, when the state is 20, the selection is 21, and the corresponding value is 3, so the optimal path is $1 \longrightarrow 2 \longrightarrow 3 \longrightarrow 4 \longrightarrow 6 \longrightarrow 8 \longrightarrow 10 \longrightarrow 11$
$\longrightarrow 12 \longrightarrow 13 \longrightarrow 14 \longrightarrow 15 \longrightarrow 17 \longrightarrow 19 \longrightarrow 20 \longrightarrow 21$, that is,

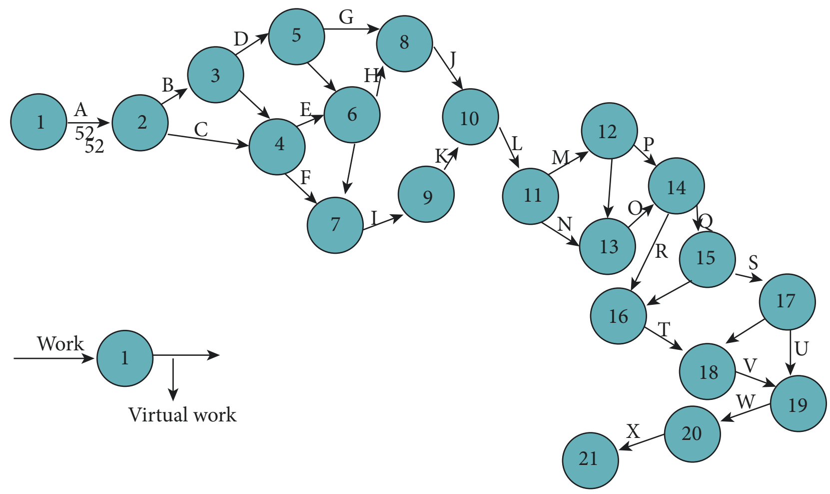

Figure 7: Project activity network diagram.

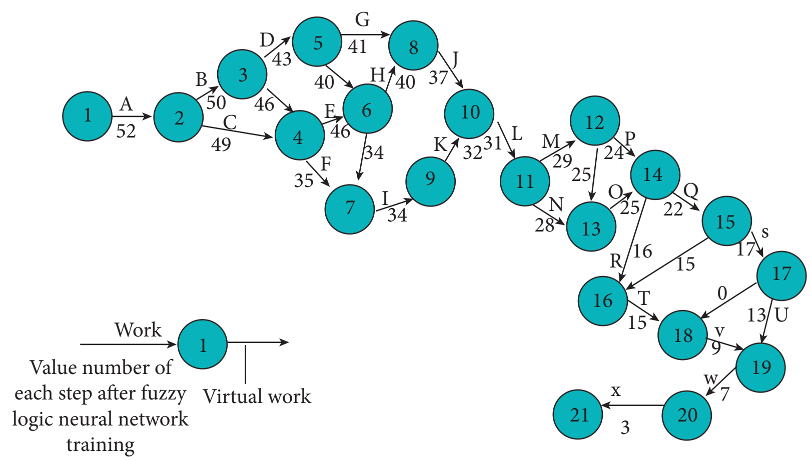

Figure 8: Network diagram of value items at each step after fuzzy depth neural network training.

A⟶B⟶C⟶E⟶H⟶J⟶L⟶m⟶o⟶Q⟶s⟶u⟶w⟶x, so the construction period is 55 days.

The traditional project schedule management technology is based on the critical path. According to the prediction results of the progress completion rate, the construction period of the construction project schedule is 57 days. Compared with the monthly schedule initially prepared, it can be seen that the construction period has been delayed to a certain extent, and the actual construction schedule will be delayed again due to resource constraints and other constraints of the traditional project management technology. The traditional project schedule management does not provide corresponding delay mitigation measures, and the completion period can only be postponed after the schedule is delayed. However, through the intelligent optimization of the construction project schedule integrating the fuzzy logic and neural network algorithm, the dynamic optimization mode of schedule is applied. When the actual construction data information of the smart site platform is updated, the completion rate of the underlying schedule that has not occurred is predicted. At the same time, the process duration of the schedule is estimated based on the prediction results of the completion rate, and then the key chain technology is used for optimization. In the way of high-frequency optimization, in the actual construction process, the project buffer is set for 5 days under accurate guidance. When the utilization rate of the buffer is not more than 2/3, the expected construction period of the key chain identified by the fusion fuzzy logic neural network algorithm is 55 days, which is 2 days less than the traditional construction project schedule management technology and will not cause construction period delay.

The above simulation project schedule results show the accuracy and feasibility of the fuzzy logic neural network algorithm in determining the critical route and construction period in the construction project schedule management. Compared with the traditional schedule management method, the fuzzy logic neural network algorithm reduces the amount of calculation and shortens the time of calculating the optimal path. It further explains the feasibility and rationality of the fuzzy logic neural network algorithm used to explore the construction project progress management.

6. Conclusion

The traditional project schedule management method makes it difficult to calculate the key route when facing the large-scale project. This paper studies this problem, proposes a building project management model based on the fuzzy logic neural network algorithm, explores intelligent schedule management methods, and takes a building project as an example for simulation experiment analysis. The planned duration of the traditional key chain technology of the project is 57 days. The duration of the scheduling process is estimated based on the prediction results of the completion rate and then optimized by the project management technology integrating the fuzzy logic neural network algorithm. The planned construction period is 55 days, which is 2 days less than the traditional construction project schedule management technology and will not cause a construction period delay. Experiments show that this algorithm is more efficient and accurate for calculating the optimal route of the project, which further explains the feasibility and rationality of this algorithm for exploring intelligent construction progress management methods. This paper applies the deep reinforcement learning method to construction progress management and verifies the effectiveness of this method through simulation experiment analysis so that the relevant departments can no longer rely on manual calculation of key routes during project construction, effectively reducing human costs, saving a lot of resources, and also providing some research ideas for some scholars.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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The purpose of this study is to serve Hunan's "Three Highlands and Four New Missions", to achieve the innovation and practice of the talent training mode of the engineering construction professional cluster and to obtain the support of the top-level design research on talent training under the natural resource background of the project engineering construction professional cluster, project number 2022G03.

References

[1] J. I. Fanrong, Q. U. Di, and F. Shang, "Study on visualization of construction schedule management under BIM Scenarios [J]," *Construction Economy*, vol. 35, no. 10, pp. 40–43, 2014.

[2] S. Yang and D. H. Zhong, "Study on construction schedule management and control method for Hydraulic & Hydropower engineering based on visual simulation[J]," *Systems Engineering-Theory & Practice*, vol. 8, no. 8, pp. 55–62, 2006.

[3] R. Tao and C. M. Tam, "System reliability theory based multiple-objective optimization model for construction projects," *Automation in Construction*, vol. 31, no. 5, pp. 54–64, 2013.

[4] P. Bhaskaran, "Progress monitoring for a highway project with cpm network plan[J]," *Indian Highways*, vol. 16, no. 4, 1988.

[5] F. Chen, R. O. Briggs, and G. Corbitt, "Project progress tracking template -using a repeatable gss process to facilitate project process management[J]," 2017.

[6] S. H. Jan, H. P. Tserng, and S. P. Ho, "Enhance construction visual as-Built schedule management using BIM technology," in *Proceedings of the ICCEM 2014:International Conference on Construction Engineering and Management*, Paris, France, November 2013.

[7] S. Sood, "Theory of constraints can change the way you manage your projects[J]," *Electronic Engineering Times*, vol. 1230, p. 40, 2002.

[8] Z. J. Wang, "Understanding the key risks in construction projects in China[J]," *International Journal of Project Management*, 2007.

[9] R. C. Newbold, *Project management in the Fast Lane: Applying the Theory of constraints[M]*, CRC Press, 1998.

[10] P. Kulkarni, S. Londhe, and M. Deo, "Artificial neural networks for construction management: a review[J]," *Journal of Soft Computing in Civil Engineering*, vol. 1, no. 2, pp. 70–88, 2017.

[11] T. Cheng, P. Wen, and L. Yang, "Research Status of artificial neural network and its application Assumption in Aviation [C]," in *Proceedings of the International Conference on Computational Intelligence & Security*, IEEE, Wuxi, China, December 2017.

[12] M.-R. Marin, M. Nicolas, and M. A. V. Villa, "An intelligent system for the acquisition and management of information from bill of quantities in building projects[J]," *Expert Systems with Applications*, vol. 63, pp. 284–294, 2016.

[13] J. K. Basu, D. Bhattacharyya, and T. Kim, "Use of artificial neural network in pattern recognition[J]," *International journal of software engineering and its applications*, vol. 4, no. 2, 2010.

[14] H. Kim, H. Hong, and D. C. Jung, "Renal parenchyma segmentation in abdominal MR images based on cascaded deep convolutional neural network with signal intensity correction [C]," in *Proceedings of the Computer-Aided Diagnosis*, February 2021.

[15] S. Mujahidin, N. F. Azhar, and B. Prihasto, "Analysis of using Regularization Technique in the convolutional neural network architecture to Detect Paddy Disease for small Dataset," *Journal of Physics: Conference Series*, vol. 1726, no. 1, Article ID 012010, 2021.

[16] Y. Y. Hong and J. H. Chou, "Nonintrusive energy monitoring for Microgrids using Hybrid self-organizing feature-mapping networks[J]," *Energies*, vol. 5, no. 12, 2012.

[17] M. Martinez-Rojas, N. Marin, and M. A. V. Miranda, "An intelligent system for the acquisition and management of information from bill of quantities in building projects," *Expert Systems with Applications*, vol. 63, pp. 284–294, 2016.

[18] H. Kerzner, *A Systems Approach to Planning, Scheduling and Controlling*, pp. 759–764, Project management, 1989.

[19] B. Liu, “Explore the importance of schedule management in the construction project management,” *Urbanism and Architecture*, vol. 119, pp. 601–610, 2014.

[20] L. Xu, “Factors affecting the construction progress and construction management[J],” *Friend of Science Amateurs*, vol. 3, no. 5, pp. 875–881, 2010.

[21] Y. R. Wang, C. Y. Yu, and H. H. Chan, “Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models,” *International Journal of Project Management*, vol. 30, no. 4, pp. 470–478, 2012.

[22] L. Zelentsov, L. Mailyan, and D. Pirko, “Methodology of making organizational and technological decisions at the stage of operational management of construction operations based on the forecasting system,” *Journal of Physics: Conference Series*, vol. 2131, no. 2, Article ID 022114, 2021.

[23] R. Jin, T. Yang, and P. Piroozfar, “Project-based pedagogy in interdisciplinary building design adopting BIM[J],” *Engineering Construction and Architectural Management*, vol. 25, no. 10, 2018.

[24] Z. M. Xiong, L. U. Hao, and M. Y. Wang, “Research progress on safety risk management for large scale geotechnical engineering construction in China[J],” *Geotechnical Engineering*, vol. 39, no. 10, pp. 3703–3716, 2018.

[25] H. Mahami, F. Nasirzadeh, A. Hosseininaveh Ahmadabadian, F. Esmaeili, and S. Nahavandi, “Imaging network design to improve the automated construction progress monitoring process,” *Construction Innovation*, vol. 19, no. 3, pp. 386–404, 2019.

[26] G. M. Sun and J. X. Yang, “Application of neural networks in Civil design engineering[J],” in *Proceedings of the 2nd International Conference for PhD students in Civil Engineering and Architecture CE-PhD*, p. 21, Cluj-Napoca, Romania, December 2014.

[27] L. X. Wang and J. M. Mendel, “Generating fuzzy rules by learning from examples[J],” *IEEE Transactions on Systems Man & Cybernetics*, vol. 22, no. 6, pp. 1414–1427, 2002.

[28] L. M. Naeni and A. Salehipour, “Evaluating fuzzy earned value indices and estimates by applying alpha cuts[J],” *Expert Systems with Applications*, vol. 38, no. 7, pp. 8193–8198, 2011.