Research Article

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

Xiaobing Yu¹ and Hengzhong Zuo²

¹Hunan Vocational College of Engineering, Zhengzhou, Hunan 410151, China
²Changsha University of Science and Technology, Changsha, Hunan 410076, China

Correspondence should be addressed to Hengzhong Zuo; 002923@csust.edu.cn

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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 re-
source-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 mathe-
matical 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 cal-
culation 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,
Rosenblatt 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 intelli-
gence 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 algo-
rithms, 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 pro-
cessing, knowledge engineering, expert systems, optimi-
zeation combination, robot control, and others [13–15].
The research results include the BP algorithm of multi-
layer 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 ef-
cient progress control, you must give different solutions
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 con-
struction 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].

(3) 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 [3]. 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 [25]. Based on the above analysis, in order to overcome the defects of traditional progress control, we must improve the traditional progress control methods and introduce deep learning and artificial intelligence into construction project progress control, which is also the new direction of progress control in the future.

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.

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

In formula (2), \( \nabla \) 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.
The 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

\[ L(w) = (R + \gamma \max_\alpha Q(s, a, w) - Q(s', a', w'))^2. \]  

(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 \( \epsilon \)-greedy \((0 < \epsilon < 1)\) select, where, \( \epsilon = 0.9 \), 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 in the project as critical path. The reward function is calculated as follows:

\[ G = \lambda G_{t+1} + R_{t+1}. \]  

(4)

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

| 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:

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

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 $1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 6 \rightarrow 8 \rightarrow 10 \rightarrow 11 \rightarrow 12 \rightarrow 13 \rightarrow 14 \rightarrow 15 \rightarrow 17 \rightarrow 19 \rightarrow 20 \rightarrow 21$, that is,
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.

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