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PSO-LSTM BASED CONSTRUCTION SCHEDULE PREDICTION METHOD FOR SHIELD TUNNELING

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With the development of shield method in water conservancy and hydropower tunnel construction, the duration prediction of shield excavation faces more complex environment and variable influencing factors. In order to consider comprehensive factors such as environment, pre-construction and shield excavation segmentation, this paper proposes a shield excavation prediction method based on particle swarm optimization long and short-term memory neural network (PSO-LSTM), and optimizes the long and short-term memory neural network (LSTM) by particle swarm optimization algorithm (PSO) to solve the problems of difficult to determine parameters of LSTM neural network model, low training efficiency and poor accuracy. The engineering example shows that the average error of the proposed simulation model is only 5.32%, which is smaller than the average error of other models. The real data proving that the proposed method can effectively predict the duration of shield excavation, which provides new data support for shield excavation duration control and resource allocation.

Keywords: shield tunneling; duration prediction; LSTM; PSO; construction schedules

1. Introduction

With the gradual development of shield method in the construction of water conservancy and hydropower tunnels [1], the duration prediction of shield tunneling faces more complex environment and variable influencing factors [2][3], and it will be challenging to reasonably arrange the working face and control the duration. The traditional schedule prediction is based on the consumption of machinery or labor hours to calculate the time required to complete a certain amount of work, in which the consumption of machinery or labor hours comes from historical data such as quotas and cost databases, but construction projects have their uniqueness and are greatly influenced by environment and site, so the

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historical data cannot fully reflect the predicted construction projects. The proposed method of time-varying construction schedule prediction reflects the real-time nature of the project progress [4]. Recurrent network simulation technology is also gradually applied to construction progress prediction, and construction progress control is becoming more and more intelligent, such as gray prediction theory [5], BIM virtual optimization method [6], BP neural network prediction [7], etc. With the development of artificial intelligence, the excellent nonlinear mapping ability and generalization ability of machine learning methods [8][9] can effectively predict time series with nonlinear and time-varying characteristics, which provides an effective technical means to establish accurate schedule prediction methods. The above studies either predict the construction schedule at the planning stage [10] or offer some constructive suggestions on on-site construction management [11], and there is no research on predicting the progress of excavation in the actual construction environment during the construction process to determine whether the construction schedule is behind. Therefore, this paper adopts Particle swarm optimization (PSO) algorithm to determine the learning rate and number of neurons of Long short-term memory (LSTM) to build the prediction model of excavation progress, avoiding the shortcomings of LSTM model in which the relevant parameters are determined empirically and are highly subjective. The LSTM model can be used to predict the duration of shield excavation, and its applicability is verified by the process of shield excavation in the Pearl River Delta water allocation project.

2. Shield tunneling progress prediction model

2.1 Problems and needs

Mapping models [12] are often established when predicting shield excavation considering factors such as geological type and operational parameters, and thus predicting construction progress, without considering the constraints of resource allocation and the effects of the actual environment (e.g., temperature and precipitation). On the other hand, according to the Supplementary Quotas for Water Resources Project Estimates (Tunnel Construction by Roadheader) issued by the General Institute of Hydropower and Water Resources Planning and Design and the Renewable Energy Quotations Station, the work content of T-2-2 cutter-type earth pressure balanced shield excavation and T-2-3 cutter-type cement balanced shield excavation includes "operating shield excavation, air supply and ventilation, measurement, dry excavation, maintenance, etc. ", the quotas divide the shield excavation into four different excavation sections: negative ring section, outgoing section, normal section and incoming section, which are considered separately. However, the commonly used shield excavation prediction model lacks the consideration of segments and does not take into account the influence of the construction situation in the previous period on the current construction.

In response to the above problems new demands are made on the progress prediction model for shield excavation: (1) the need to quantify and take into account the construction conditions of the previous period. (2) the need to effectively consider the impact of different excavation sections (negative loop, outgoing hole, normal, and incoming hole) on the construction progress. (3) the need to consider the constraints of resource allocation and quantify the environmental impact.

In order to meet the above needs, this paper proposes a new simulation model for shield tunneling construction considering segments, as shown in Fig. 1, which accurately obtains the unit duration by establishing a high-precision prediction method for the time used to fix the tunneling distance, and incorporates influencing factors such as geological conditions, staffing, temperature and rainfall into the model to improve the accuracy of the simulation model and its application effect in engineering practice. The mathematical model consists of 3 parts.

①Input: Define the model input parameters, which can be divided into two main parameter sets, factor parameters and algorithm parameters. The factor parameters include the influence of the previous period, the influence of different excavation sections, and the influence of the environment.

②Model: PSO-LSTM method for predicting construction period.

③Output: The output result of the progress simulation model is the stage duration.

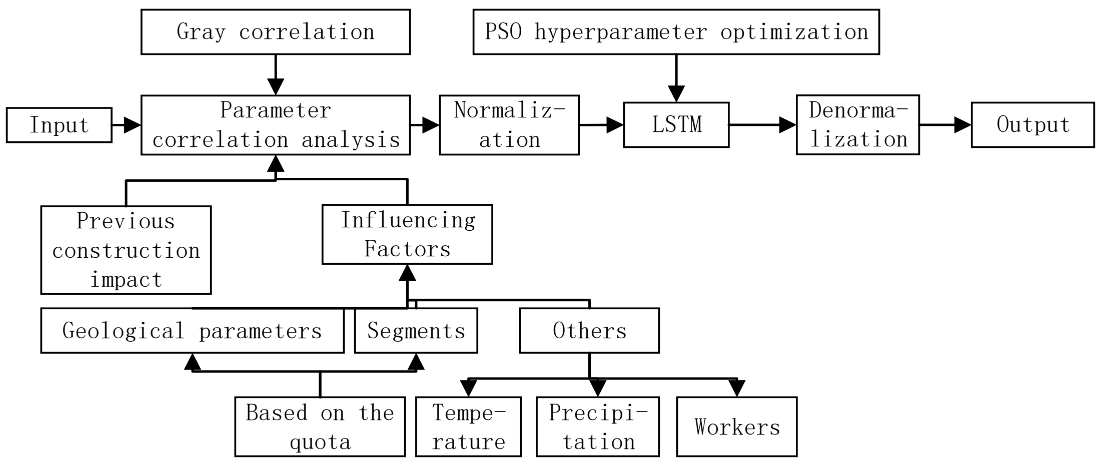

Fig. 1. Algorithm flow chart

2.2 Screening of strongly correlated factors

After the initial qualitative analysis to find the variables, the correlation degree analysis of the initially screened influencing factors was performed by the gray correlation method to further screen the strongly correlated influencing factors.

Step 1: All data are dimensionlessly processed by the mean method, and the correlation coefficient of the ith sample of the tth factor and the corresponding construction efficiency is:

$$\zeta_t(i) = \frac{\min_t \min_i \left|Y(i) - X_t'(i)\right| + \eta \times \max_t \max_i \left|Y(i) - X_t'(i)\right|}{X_t'(i) + \eta \times \max_t \max_i \left|Y(i) - X_t'(i)\right|} \tag{1}$$

In equation (1), Y(i) is the ith sample of construction efficiency and η is the discrimination coefficient, which is taken as 0.5 here.

Step 2: The correlation between the tth variable and construction efficiency is

$$r_t = \frac{1}{n}\sum_{i=1}^{n} \zeta_t(i) \tag{2}$$

It is generally considered that when $0 \le r_t \le 0.35$, the correlation between factors is low. When$0.35 \le r_t \le 0.65$, the correlation between factors is medium. When $0.65 \le r_t \le 1$, the correlation is strong. The factors with strong correlation with construction machinery construction efficiency are selected to establish the neural model.

2.3 PSO-LSTM-based shield excavation duration prediction method

The LSTM model can memorize the value of variable time length and transfer the information, which can better predict the duration change. In order to determine the parameters in the LSTM model, this chapter uses PSO to determine the learning rate and the number of neurons of the LSTM model to build the optimal structure for predicting the duration of shield excavation.

2.3.1 Long and short-term memory neural network (LSTM) fundamentals

Step 1: The forward propagation process is classified according to the LSTM cell structure.

① Input gates:

$$a_t = \tanh\left(W_a \cdot x_t + U_a \cdot out_{t-1} + b_a\right) \tag{3}$$

$$i_t = \sigma\left(W_i \cdot x_t + U_i \cdot out_{t-1} + b_i\right) \tag{4}$$

In Eqs. (3) and (4), x_t is each influence factor at time t,and out_t is the output at time t-1 from the previous time at time t. W_a is the weight, U_a represents the degree of influence at time t-1, and b_a represents the error not represented by the influence factor, and the three variables keep changing with the back propagation in training.

② Forgetting gate:

$$f_t = \sigma\left(W_f \cdot x_t + U_f \cdot out_{t-1} + b_f\right) \tag{5}$$

In Eq. (5), σ is the activation function, which determines the discard and retention of information by 0~1, the closer to 0 the more biased the discard. W_f, U_f and b_f are the weights, which keep changing with back propagation in training.

③ Output gates.

$$o_t = \sigma\left(W_o \cdot x_t + U_o \cdot out_{t-1} + b_o\right) \tag{6}$$

In Eq. (6), x_t is each influence factor affecting shield excavation at moment t. out_t is the cumulative excavation length at t-1. W_o, U_o and b_o are weights, which keep changing with back propagation in training. Then Cell state and cell output are: $state_t = a_t \odot i_t + f_t \odot state_{t-1}$, $out_t = \tanh\left(state_t\right) \odot o_t$

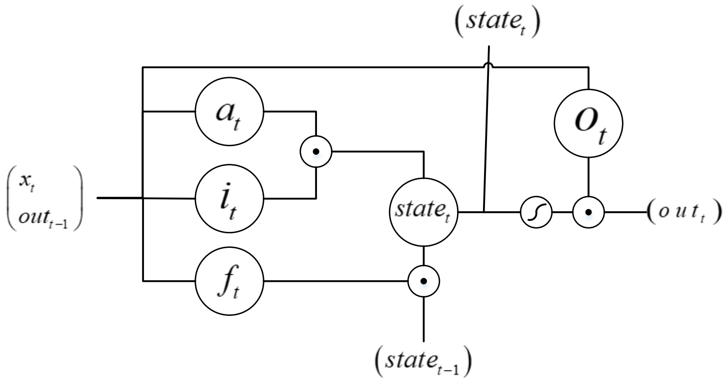

Fig. 2. Structural unit diagram of LSTM model

Step 2: The backpropagation process of the model is shown in Fig. 2 of the structural unit, and the error variables are trained by backtraining. According to $W_{new} = W_{old} - \lambda \frac{\alpha L}{\alpha W}$, which new weights can be introduced and brought to the next time step for repeated training.

2.3.2 PSO-LSTM method and process for predicting work hours

As mentioned before, the LSTM model uses gradient descent to set the weight bias, where the learning rate and the number of neurons in the hidden layer are the key parameters. These parameters are generally determined empirically, which makes the efficiency and accuracy of the model fluctuate widely. In this paper, we use PSO algorithm to optimize the learning rate and the number of neurons in the hidden layer of LSTM, and the PSO algorithm has good performance and can obtain the results faster. The specific steps are as follows.

Step 1: Construct the input matrix.

Construct the input matrix. The LSTM model can memorize the values of variable time length and transmit the information, and the continuous efficiency time efficiency can be added to better predict the change of duration. m before the moment t is used as the sample, and m is determined by the AIC criterion.

$$AIC = 2k + n\ln\left(\frac{RSS}{n}\right) \tag{7}$$

In Eq. (7), k is the number of influencing factors, n is the number of samples, RSS is the residual sum of squares, and k is m when the AIC is smallest. then the input matrix can be obtained as follows.

$$X = \begin{bmatrix} y_1 & \cdots & y_m & x_{m+1} \\ y_2 & \cdots & y_{m+1} & x_{m+2} \\ \vdots & \vdots & \ddots & \vdots \\ y_{N-n-m+1} & \cdots & y_{N-n} & x_{N-n+1} \end{bmatrix} \tag{8}$$

In Eq. (8), X is the input matrix of the digging efficiency prediction model. y_i is the digging time at the ith moment, which is determined by the previous m digging decreases and x_i. And x_i is the other influencing factors at the ith moment.

Step 2: Randomly generate the positions and velocities of the population particles, where the positions of the particles are set as two-dimensional vectors representing the learning rate and the number of neurons of the LSTM model.

Step 3: Set the fitness function as

$$R = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{9}$$

In Eq.(9), y_i is the predicted unit duration and $\hat{y}_i$ is the predicted unit duration.

Step 4: Population update. The positions and velocities of the particles within the population are updated by comparing the fitness.

$$v_i^{t+1} = wv_i^t + c_1\varsigma\left(p_i^t - x_i^t\right) + c_2\eta\left(p_g^t - x_i^t\right) \tag{10}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{11}$$

In Eq. (10), w is the inertia factor, and the larger w is, the stronger the global capability, which is obtained based on the decreasing weight strategy by the number of iterations. p_i^t is the individual optimal setup parameter at time t, i.e., the individual optimal setup parameter at time t. p_g^t is the global optimal setup parameter at time t. In Eq. (11), x_i^t is the two-dimensional vector of the particle's position, learning rate and number of neurons; v_i^t is the particle's velocity.

Step 5: Set the optimal parameters and use the LSTM model to predict the unit duration of 50m of tunnelling, and project the time required to complete a tunnel with a known total tunnel length.

3. Engineering Example

The shield tunneling of the Pearl River Delta Water Resources Allocation Project is used as the research object to carry out a simulation model study of shield tunneling construction. The project is located in the south of China, which is warm and rainy, with abundant light and heat, long summer and short frost period. Throughout the year, the rainy season is from April to June, and the weather is hot and typhoon-prone from July to September. The total length of the tunnel is 1690m, the diameter of the tunnel is 4.1m, the shield machine is a mud-water balance shield, and the planned construction period is 294 days.

3.1 Data Acquisition and Processing

3.1.1 Data source

The data are obtained from the Pearl River Delta Water Resources Allocation Project, China. And the Pearl River Delta Water Resources Allocation Project diverts water from the Xijiang River system in Guangdong Province to the eastern part of the Pearl River Delta for the purpose of solving the problem of water shortage for urban life and production in Nansha District, Guangzhou, Shenzhen and Dongguan City, and the total length of the water transmission line is 113.1 kilometers. The project adopts the method of deep-buried shield construction, which is built underground at a depth of 40 meters to 60 meters.

The temperature and precipitation data at the construction site are selected and integrated and averaged into the daily temperature and daily precipitation for completing the unit length of excavation. For example, in the negative ring section, it took a total of 23 days to dig 50m, and a total of 57.2mm precipitation was received in these 23 days, so the average daily precipitation was 2.47mm (57.2÷23=2.47). The segment data is determined according to the "Supplementary Quotas for Estimated Budget of Water Resources Process (Tunnel Construction by Roadheader)" (Water General [2007] No. 118) issued by the Ministry of Water Resources. The geological situation, manual according to the actual record to obtain the average value of the excavation of 50m, data collation can be seen that the shield excavation in the normal section of the most time, the geological situation is also more consistent, shield excavation to 425-850m when the precipitation is more.

3.1.2 Correlation analysis of influencing factors

The gray correlation between factors such as segmentation, geology, precipitation, temperature, workers and average duration of 50m per excavation is calculated and the results are shown in Fig. 3. Except for temperature, the correlation degree of all factors is greater than 0.8, which is used to establish LSTM neural network as a strong influencing factor. Generally speaking, temperature is an important factor affecting tunneling efficiency, but the correlation between here and shield tunneling efficiency is not strong, probably because the temperature peaks and valleys at the construction site do not differ much, and the temperature is moderate and less undulating throughout the year, so it has less influence on shield tunneling.

3.2 Duration prediction

3.2.1 Parameter Setting

The optimal learning rate and number of neurons are obtained by training test with PSO-LSTM model. The particle population is set to 20, the maximum number of iterations is 30, the range of neurons is 1-50, the range of learning rate of gradient descent is 0.1-0.9, and the initial velocity and position are determined randomly.

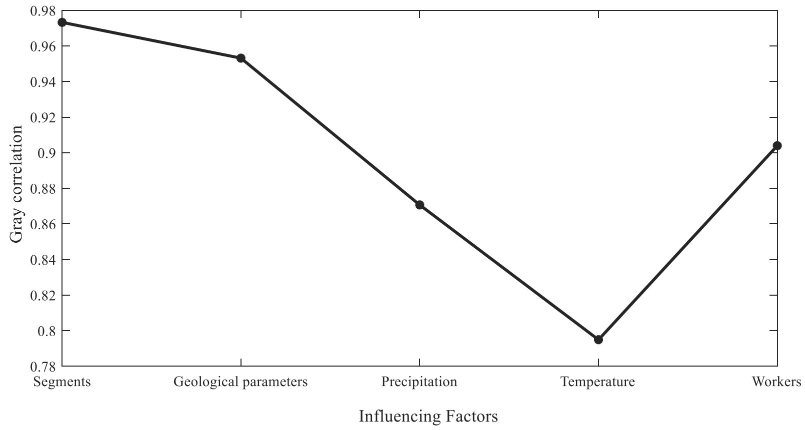

Fig. 1. Gray correlation

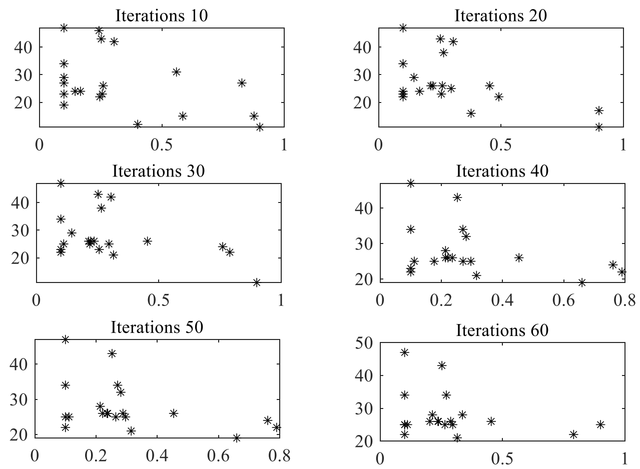

Fig. 2. PSO-LSTM model training results

The number of hidden layers is 1. The training is performed with the above data, and the results are shown in Fig. 2. The particle swarm converged at the 60th iteration, and the optimal parameters for the PSO-LSTM model were a learning rate of 0.236 and the number of neurons of 26.

3.2.2 Duration prediction

As shown in Fig. 3, when the training data accounts for 60% of the total, the difference between the time used for 50m of shield boring and the actual is large; while the larger the percentage of training data, i.e., the more training data, the smaller the difference between the time used for 50m of shield boring and the actual. In other words, as the construction progresses, the prediction of the model will gradually approach the actual. Based on the predicted unit time of tunnelling, the total duration of a tunnel at the completion of 1690m of tunnelling can be obtained, with the training data accounting for 90% of the total duration being the closest to the actual duration.

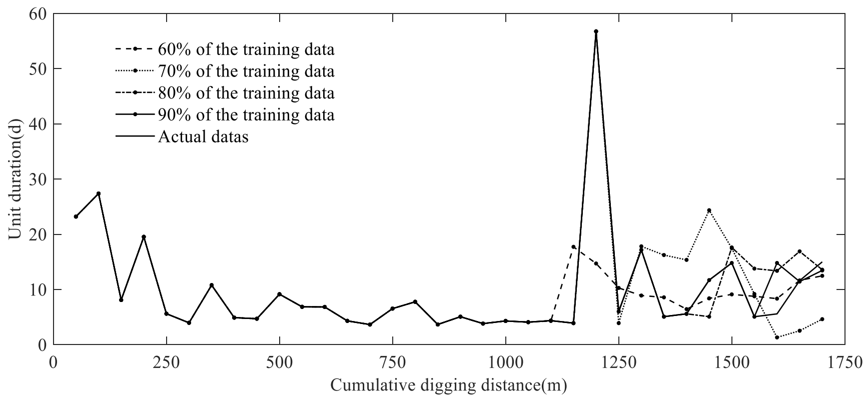

Fig.3 Comparison of predicted time for shield tunneling 50m

3.3 Comparison and Discussion Analysis

3.3.1 Comparison of prediction methods

The tunnel boring was analyzed, and the relative errors at 60%, 70%, 80% and 90% of the total tunnel length were calculated for the completed boring length, i.e., 10%-40% of the predicted total tunnel length, and the results are shown in Table 1.

Table 1

Training results and relative error

Percentage of training data	No.1	No.2	No.3	No.4	No.5	Average duration	Relative error
60%	308.43	308.87	303.32	298.96	301.14	304.14	9.70%
70%	353.90	351.30	355.79	352.51	353.44	353.39	4.92%
80%	345.29	359.49	340.76	364.46	349.97	352.00	4.51%
90%	343.09	345.34	343.90	344.74	344.46	344.31	2.22%

The average relative error of the PSO-LSTM model prediction results is 5.32%, and the difference between the 5 training results is not significant, the amount of training data has more influence on the training results: the error of training results decreases with the increase of training data, and the error is larger when the training data accounts for 60%, which is 9.7%; the error of training results is stable at about 5% when the training data accounts for 70% and 80%; the error of training results when the training data accounts for At 90% of the training data, the result error is the smallest, only 2.22%. The comparison with other models is shown in Fig. 4.

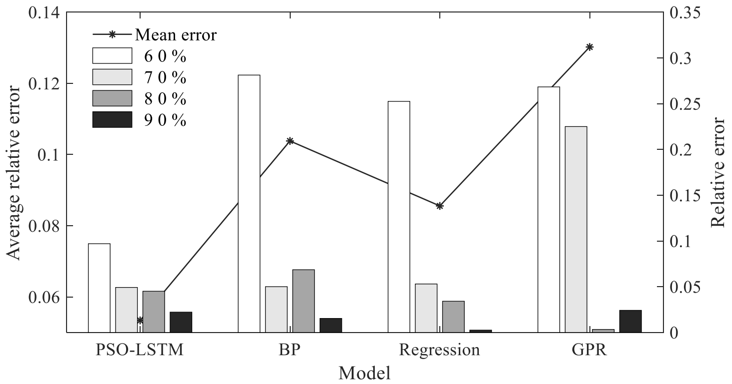

Fig. 4. Comparison of prediction results of different models

(1) Comparing the average relative errors of the prediction results of the four models of nonlinear regression, BP neural network, and Gaussian process regression, it can be found that the PSO-LSTM model has the smallest error and the most stable prediction. (2) The accuracy of nonlinear regression depends on the function selection and the prediction is not stable. (3) The BP model approximates the minimum error by gradient descent method and has the problems of slow convergence and local optimization. (4) The Gaussian process regression model has a large relative error when the training data is small, and when the training data is sufficient, although the relative error of the prediction results is smaller than that of the PSO-LSTM model, the computational efficiency of this model is low due to the computational complexity of the Gaussian regression model.

3.3.2 Segmentation impact on schedule

The impact of segmentation on the duration is shown in Fig. 5, and the analysis shows that:

(1) in the impact layer geology, the unit duration from short to long is normal section, negative ring section and inlet section; in the waterway, the unit duration from short to long is outgoing section, normal section and negative ring section; the average unit duration is outgoing section, normal section, negative ring section and inlet section; (2) when the staffing is similar, the unit duration also has the above

rule: from long to short is outgoing section, normal section, inlet section and negative ring section.

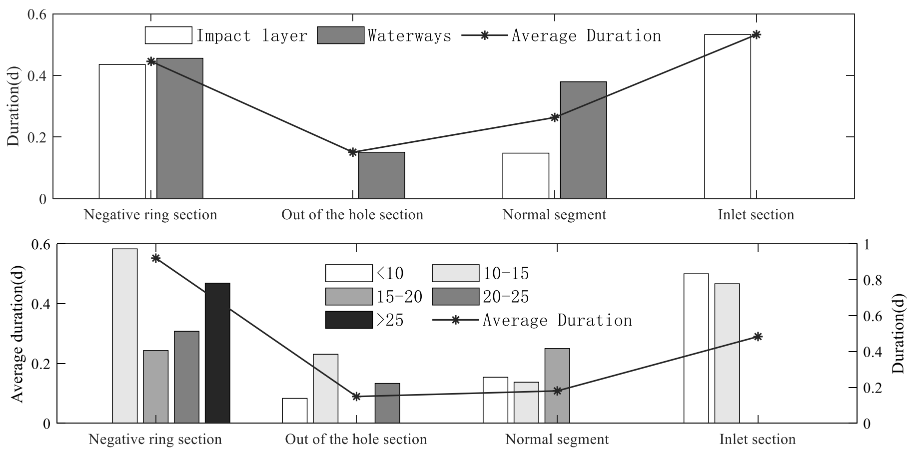

Fig. 5. Impact of segmentation on the construction period

(3) The unit time consumption of mud and water balance shield in 4m diameter tunnel is from small to large: normal section (0.1532 days/m), negative ring section (0.1704 days/m), inlet section (0.2839 days/m), outlet section (0.3617 days/m); (4) The unit time consumption of outlet section and normal section in the quota is larger than the actual time consumption, because the quota is the social (4) The table time consumption of the outgoing hole section and normal section in the quota is larger than the actual time consumption because the quota is the average level of the society and the enterprise construction efficiency is higher; the table time consumption of the negative ring section and the incoming hole section is smaller than the quota because the negative ring section includes the parts of the cart down the well and the pipeline connection, which is less efficient; the incoming hole section has to consider the construction of the receiving well and there is downtime, which is less efficient.

3.3.3 Model Application

The long shield excavation cycle and complex objective environment make the construction duration difficult to predict. The proposed shield excavation duration simulation model can effectively predict the duration of shield excavation, which provides new data support for reasonable layout of working face, arrangement of personnel and machinery allocation and control of duration.

To illustrate the effectiveness of the method proposed in this paper, the start time and planned duration of different tunnels and the predicted duration according to the prediction model are shown in Table 2 for this water transmission project as an example. Due to force majeure factors such as epidemics, the actual progress differs greatly from the schedule, and the start time is also different from the plan, which makes us only compare the prediction accuracy of the model by comparing the actual duration.

Table 2

Projected duration of different tunnels

No.	Planned start time	Planned duration	Actual start time	Simulated duration	Actual duration	Relative error
1	2020/9/8	674	2020/9/20	715	713	0.28%
2	2020/10/8	674	2020/10/24	621	617	0.65%
3	2020/11/28	601	2021/1/4	591	589	0.34%
4	2020/12/8	596	2020/12/15	618	611	1.15%
5	2020/12/15	629	2021/2/16	524	504	3.97%
7	2021/4/20	498	2021/4/14	493	467	5.57%
8	2021/5/5	483	2021/3/19	478	467	2.36%
9	2021/3/9	408	2021/3/11	481	473	1.69%

From Table 2, we can know that the overall prediction result of the tunnel with serial number 7 is relatively not very good. The diameter of the tunnel is 6m, the total length of the tunnel is 2394m, and the shield machine is a soil-pressure balance shield machine. Analyzing the process of the shield machine, we can find that in addition to the normal maintenance and grouting, there are long periods of shutdowns for rectification, and there are 4 shutdowns for rectification during the excavation period, with an average shutdown time of 12 days each time. These stoppages are not caused by construction but by inspection and other artificial influences, which did not occur in the subsequent construction, thus resulting in an error of 5.32%.

Based on the prediction method proposed in this paper, on the one hand, the end time can be calculated based on the actual start time and the predicted duration, and if the duration requirement cannot be met, the working surface can be increased and the construction organization can be adjusted in time to shorten the duration. On the other hand, the resource allocation can be adjusted according to the model prediction, so as to reduce the waste of resources when the schedule requirement is met.

4. Conclusion

In view of the difficulty of shield excavation duration prediction, a shield excavation duration prediction method based on PSO-LSTM is proposed, which is compared and verified with other prediction models in an engineering example of shield construction in the Pearl River Delta, and the following conclusions are obtained.

(1) The efficient search and global optimum capability of the particle swarm optimization algorithm is used to optimize the LSTM neural network model, which improves the training efficiency and accuracy of the LSTM model and thus achieves the prediction of the shield boring duration.

(2) Shield excavation duration is related to shield excavation segments, geological conditions, staffing, rainfall and other factors, among which segments (negative ring, outgoing hole, normal, incoming hole) have the greatest impact on the duration, and a good articulation of each segment in the actual construction is conducive to shortening the duration and improving the construction efficiency.

The PSO-LSTM-based shield excavation duration prediction model proposed in this paper provides data support for shield excavation construction schedule control and provides new ideas for shield excavation schedule management and resource allocation. In addition, further research is needed on the influencing factors of step size in the LSTM neural network model. In further research, it is hoped to consider the influencing factors of unconventional behavior without affecting the simplicity of the model.

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