Research on Construction Project Cost Prediction Model Based on Recurrent Neural Network

Yanqin Wang\textsuperscript{1a}, Xu Ning\textsuperscript{1b}, Dong Zhen\textsuperscript{2c}, Wang Yong\textsuperscript{2d}, Hongshan Zhang\textsuperscript{2e}

\textsuperscript{1a}State Grid Hebei Electric Power Company Economic Research Institute, Shijiazhuang, Hebei 050000
\textsuperscript{1b}State Grid Hebei Electric Power Company, Shijiazhuang, Hebei 050000

Abstract: At present, the conventional construction project cost prediction method mainly constructs the cost prediction model by quantifying the engineering information, which leads to poor prediction effect due to the lack of construction of cost prediction index system. In this regard, the research of construction cost prediction model based on recurrent neural network is proposed. By classifying and integrating the construction project cost concepts, constructing the prediction index system, combining with the recurrent neural network algorithm, constructing the excitation function and calculating the initialization threshold, and finally constructing the prediction model. In the experiment, the proposed method is verified for the prediction accuracy. After the experiments, it can be proved that when the proposed model is used to predict the engineering cost, the root mean square error of the model output is small and has a more ideal prediction accuracy.

1. Introduction

Construction project cost mainly includes two aspects, one is the investment amount or construction project cost, and the other is the contract price or contracting price. The prediction of construction project cost is mainly through the unit index method, that is, according to the characteristics, structure and scale of the project, the corresponding prediction index is applied, calculated and summarized\textsuperscript{[1]}. The whole process is relatively complicated and time-consuming; at the same time, the prediction scheme also has the problem of difficult to guarantee the prediction accuracy. Using the unit index method for construction cost prediction, the index system used is unified by the local or industry, while the characteristics, structure and scale of the project, the corresponding prediction index is applied, calculated and summarized\textsuperscript{[1]}. The whole process is relatively complicated and time-consuming; at the same time, the prediction scheme also has the problem of difficult to guarantee the prediction accuracy.

The second meaning, contract price (contracting price), refers to the contractual price formed in the process of implementing the construction project\textsuperscript{[2]}. The contract price is for Party B, the contractor and the issuer. Since there is a certain ambivalence in the pursuit of interests of both parties, for example, in engineering projects, Party A wants to pay less money for investment, while Party B wants to earn more profit, both parties seek to obtain a suitable contract price in their favor by virtue of the market and ensure that the price payment is honored, both parties have their own price management problems in engineering projects. Although there are few highway cost prediction methods, the use of recurrent neural networks to predict highway costs has its unique advantages. Previous highway cost forecasting methods include traditional forecasting methods and modern forecasting methods\textsuperscript{[3]}. Traditional forecasting methods include unit production capacity estimation method, production capacity index estimation method, Langer coefficient method, etc., which only reach the level of estimation; modern forecasting methods include regression analysis method, exponential smoothing method, fixed ratio regression method, Markov forecasting method, trend extrapolation method, fuzzy mathematical method, etc., which either need a large amount of data to do forecasting support or need experts to make subjective judgments, which do not meet the feasibility and objectivity of forecasting. Most of them are linear models, which cannot reflect the complex nonlinear relationship between factors affecting cost and cost, and the accuracy of prediction results needs to be considered. This paper takes construction cost estimation as the entry point, and through scientific and reasonable control of construction cost, rational use of funds in the actual construction of building projects, in order to achieve the purpose of significantly improving the efficiency and effectiveness of the knowledge management system. The accuracy and precision of construction project cost determines whether the enterprise can continue to survive and develop, and is significant for the cost control of construction engineering construction enterprises, as well as the bidding work of construction projects\textsuperscript{[4]}. 

\textsuperscript{a}timreale@163.com, \textsuperscript{b}ynstp.tim@gmail.com, \textsuperscript{c}SM_3099523591@qq.com, \textsuperscript{d}18966802300@sohu.com, \textsuperscript{e}lrhin@163.com
2. Construction project cost prediction index system determination

In order to make accurate prediction of construction project cost, it is necessary to establish a prediction index system first. In this paper, combined with the specific reality of construction projects, the 23 main influencing factors extracted that affect construction project cost are classified and defined in connotation, some of which have a low degree of influence on construction cost [5], while some of them can be replaced with influencing factors that can affect construction project cost more directly, and some concepts overlap and need to be merged.

The neural network predictive control system is based on the generalized predictive control and adds a neural network to calculate the error between the predictive model and the controlled object. The basic principle block diagram is shown in Figure 1.

Figure 1 Structure diagram of neural predictive control
Some of them are the results of the influence factors as a direct reflection of the construction cost. Therefore, the indicators for construction project cost prediction in this section are selected as shown in Table 1 below [6].

Table 1 Construction project cost prediction index system

<table>
<thead>
<tr>
<th>Construction project cost forecast index</th>
<th>Reason for adjustment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Above ground floor area</td>
<td>Conceptual overlap</td>
</tr>
<tr>
<td>Underground building area</td>
<td></td>
</tr>
<tr>
<td>Foundation type</td>
<td>High impact on pile type</td>
</tr>
<tr>
<td>Pile type</td>
<td>Relatively low impact on total construction cost</td>
</tr>
<tr>
<td>Structure type</td>
<td>Seismic rating will directly affect the building material selection</td>
</tr>
<tr>
<td>Seismic rating</td>
<td>Greater impact</td>
</tr>
<tr>
<td>Project Management Level</td>
<td>The degree of impact is low</td>
</tr>
<tr>
<td>Difficulty of earthwork treatment</td>
<td>Building unit cost has a large impact on the overall project cost</td>
</tr>
<tr>
<td>Façade material</td>
<td></td>
</tr>
<tr>
<td>Number of building units</td>
<td></td>
</tr>
<tr>
<td>Above-ground and below-ground floor height</td>
<td></td>
</tr>
<tr>
<td>Average price change of concrete</td>
<td>Significant impact factor</td>
</tr>
</tbody>
</table>

Average price change of steel reinforcement [Cost per square]

Through the classification and integration of concepts, 15 factors affecting engineering cost are extracted as the control objects for research, and each factor is defined in connotation, and the selected indicators have reference standards in the field of engineering cost, and the selected indicators are also the reference objects recognized by the industry [7]. After the definition of the connotation of the indicators, it is still necessary to quantify the indicators and set the data of each indicator into specific values to facilitate the later research [8].

3. Determination of the excitation function and the initialization threshold

The transfer function in the recurrent neural network model is usually taken as a differentiable monotonically increasing function, including logsig(), tansig() and the linear function purelin(). Recurrent neural networks usually use S-type functions for the implicit layer and linear excitation functions for the output layer [9]. S-type functions are graphical like S-shaped functions with nonlinear and derivable characteristics, and S-type functions can gain control over the signal to prevent the network from entering saturation. logsig() and tan sig() are commonly used S-type functions. The methods of initializing the weights and thresholds are randomization method and Nguyen-Widrow method. Usually the computational results show that the randomized method does not seem to be very suitable, and in the face of more complex nonlinear systems, the randomized method leads to computational inefficiencies [10]. However, the N-W method with initialized weights and thresholds proposed by Nguyen and Widrow can achieve a significant improvement in computational efficiency. The resulting equations for the initialized weights W and the initialized threshold b are shown below.

\[ W = 0.7m \cdot \text{rand}(m, n) \]  \hspace{1cm} (1)
\[ b = 0.7l(m, n) \cdot \text{normr}(m, n) \]  \hspace{1cm} (2)

where n, m and l represent the number of nodes in the input, implied and output layers, respectively, \( \text{rand}(m, n) \) represents the random number matrix, and \( \text{normr}(m, n) \) represents the normalized normalized matrix of the matrix M. In order to make the prediction more reasonable, the actual engineering data needs to be normalized and normalized so that the data used for training can be as realistic as possible. Among these two types of variables, text-based variables cannot be directly used as input layer variables [11], which need to be quantified; numerical variables need to be normalized to between [0, 1] due to inconsistent magnitudes. The data preprocessed by the above methods are more easily trained and learned by the network. In this regard, the values need to be normalized, and the specific calculation formula is as follows.

\[ X_i = \frac{X_i - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \]  \hspace{1cm} (3)
Where, $X_{\text{max}}$ and $X_{\text{min}}$ represent the maximum and minimum values of the sequence, respectively. The above steps are used to construct the excitation function and calculate the initialization threshold of the recurrent neural network for the subsequent construction of the cost prediction model.

4. Construction and training of cost prediction model based on recurrent neural network

Based on the recurrent neural network, the cost curves and cost influencing factors of $w$ days before the forecast date are used to predict the cost situation on the forecast date, and the model output value is set as the forecast cost value on the forecast date, as shown in the following formula\textsuperscript{[12]}:

$$L_d = t\{l_{d,0}, l_{d,1}, \ldots, l_{d,t}\}$$  \hspace{1cm} (4)

Where $t$ represents the sampling time interval and $l_{d,t}$ represents the predicted value. Through the above analysis of the cost prediction evaluation index, it is concluded that the main factors affecting the cost are engineering variables $L_d$, special events $E_d$ and other factors $F_d$. The resulting cost prediction model expression is shown as follows\textsuperscript{[13]}.

$$I_{\text{input}} = \text{LSTM}\{L_d, E_d, F_d\}$$  \hspace{1cm} (5)

After constructing the prediction model, the model is trained, which includes three stages of data pre-processing, model training and model evaluation. Data pre-processing mainly includes 2 steps of data vectorization and standardization. The neural network is based on linear algebra theory, so it cannot be trained on the original data directly, and the original data needs to be converted into vectors before training. Data vectorization is performed by splicing $l_{d,t}$ with $L_d$, and the spliced data is transformed into a vector\textsuperscript{[14]}. The BPTT algorithm is used to train the LSTM network for cost prediction. The training objective is to adjust the network parameters so that the network output is as close to the true value as possible. First, the parameters of the recurrent neural network are initialized, and then the training data are fed into the recurrent network to calculate the output values of the network. The error between the predicted and actual values of the network is calculated by using the loss function, and the gradient value of the network parameters to the loss function is calculated according to the error, and the recurrent neural network parameters are adjusted according to the gradient. Finally, determine whether the optimal number of rounds has been reached, if the optimal number of rounds has been reached then output the result and end the model training, if the optimal number of rounds has not been reached then recalculate the recurrent network output value\textsuperscript{[15]}.

5. Testing and Analysis

5.1. Test Preparation

In order to prove that the prediction effect of the research of construction cost prediction model based on recurrent neural network proposed in this paper is better than the conventional construction cost prediction model, after the theoretical part is designed, an experimental session is constructed to verify the actual prediction effect of this construction cost prediction model. In order to improve the reliability of the experimental results, two conventional construction cost prediction models are selected as the objects of comparison in this paper, and the effectiveness of this paper's method is proved by comparing the experimental results of the three methods. The conventional methods selected for this experiment are the construction cost prediction model based on machine learning and the construction cost prediction model based on data mining.

This experiment collected the forecast indexes of highways in a province in the past five years, completed the data collection, and used three cost prediction models in the actual engineering cases for empirical research. By inputting the engineering data of the actual engineering case into the three cost prediction models, the prediction results of the cost models were tested by using the traindx function in MATLAB software.

The training process of the cyclic neural network is shown in Figure 2. After the 80th iteration, the model enters the convergence state, and the loss value is about 0.2, indicating that it has good performance.

![Figure 2: Training process of the model](image)

The prediction results of the three prediction models are shown in Figure 3. As can be seen from the figure, the prediction result of the model in this paper is closest to the real value and has better prediction ability.

![Figure 3: Prediction results of the three models](image)
5.2. Analysis of test results

The evaluation index selected for this experiment is the prediction accuracy of the cost prediction model, and the specific measure is the root mean square error (RMSE) of the prediction results, the lower the value represents the better the prediction effect of the model, and the specific calculation formula is shown below.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\bar{L}_i - L_i)^2}
\]  

(6)

Where \( N \) represents the total number of training samples, \( \bar{L}_i \) represents the predicted manufacturing value, and \( L_i \) represents the actual manufacturing value. The specific experimental results are shown in the following figure.

![Figure 4 Comparison results of root mean square error of cost forecast](image)

Analysis of Figure 4 shows that the root mean square error of the cost prediction results of different cost models differs in the cost prediction of the same set of construction project data. The numerical comparison shows that the prediction results of the model proposed in this paper are closer to the actual cost situation, and the root-mean-square error of cost prediction is below 4%, which has a high accuracy of cost prediction. In contrast, the prediction results of the two conventional prediction models are much different from the actual situation, with the root-mean-square error value above 5%. It can be proved that the method proposed in this paper can effectively predict the cost of construction projects, and the convergence of the model is good.

6. Conclusion

The construction cost prediction model proposed in this paper is effectively combined with the recurrent neural network algorithm, and the prediction effect is proved to meet the expectation and can be put into use by experiment. However, since there are many factors affecting the construction project cost, and the factors are interrelated, there is a certain difficulty in the selection of fingers.

References
