Research on Modern Construction Cost Economic Management Based on the Whole Process of Genetic Algorithm

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Abstract. Genetic algorithm and neural network are both ideas and algorithm skills. The flexibility of this method provides a stage for many researchers and applications. In view of the complexity of general construction engineering valuation problems and the advantages of genetic algorithm and neural network algorithm, this article proposes a new construction engineering valuation model. Taking the actual residential project as an example, the feasibility and reliability of the genetic algorithm to optimize the neural network model are verified, and it is better than the simple neural network model, which provides an effective method for actual project investment estimation.

Key words. Genetic algorithm, neural network, engineering structure, engineering cost.

1. Introduction
There are many factors that affect the cost of construction projects, the composition is relatively complex, and there is a complex non-linear relationship between cost and elements. Practical engineering cost estimation methods have become an urgent need of the construction industry. Zhou Liping uses BP neural network to predict construction project valuation [1]. Hu Zhenfeng uses a fuzzy mathematics method to estimate the project cost. Due to the non-linear relationship between construction engineering structure and engineering cost, the use of traditional methods often requires past experience, a large amount of engineering information and tedious calculations. In this paper, a set of fast, simple and practical hybrid GA-ANN model is used to evaluate the construction project based on the construction project structure.

2. Project valuation forecast based on hybrid GA-ANN model
2.1. Neural network model
The research of NN belongs to the category of artificial intelligence. NN is a simulation of the brain structure and the study of intelligent behavior from a micro level. Therefore, NN is usually a large-scale network structure formed by a large number of artificial neuron cells connected to each other. Each artificial neuron cell (also called processing unit or network node) has only simple nonlinear processing capabilities, but through their interconnection and interaction, they can exhibit complex intelligent processing functions or nonlinearities Processing power. The neural network is composed of simple
units and is a nonlinear model structure for large-scale parallel information processing. The three-layer neural network can realize most nonlinear mapping [2]. Figure 1 shows the schematic diagram of the neural network model.

![Schematic diagram of neural network model](image)

**Figure 1.** Schematic diagram of neural network model

Here, a three-layer feedforward neural network is used for system modeling. Let \( m, q, \) and \( k \) be the number of nodes in the input layer, hidden layer, and output layer, respectively, \( \{ w_{ij} \mid i = 1, ..., q, j = 1, ..., m \} \) is the connection weight from the input layer to the hidden layer, \( \{ v_{ij} \mid i = 1, ..., k, j = 1, ..., q \} \) is the connection weight from the hidden layer to the output layer, \( \{ x_i \mid i = 1, ..., m \} \) is the input signal, \( \{ u_i \mid i = 1, ..., q \} \) is the state of the hidden layer node, \( \{ z_i \mid i = 1, ..., k \} \) is the output signal, \( \{ \theta_i \mid i = 1, ..., q \} \) is the hidden layer node threshold, \( \{ \varphi_i \mid i = 1, ..., k \} \) is the output layer node threshold, \( f(\bullet) \) is the excitation function, then the hidden layer and output layer node outputs are respectively

\[
u_s = f \left( \sum_{j=1}^{m} w_{sj} x_j + \theta_s \right) \quad s = 1, \Lambda, q
\]

\[
z_i = \sum_{s=1}^{q} v_{is} u_s + \varphi_i \quad i = 1, \Lambda, k
\]

Or can be written as

\[
z_i = \sum_{s=1}^{q} v_{is} f \left( \sum_{j=1}^{m} w_{sj} x_j + \theta_s \right) + \varphi_i \quad i = 1, \Lambda, k
\]

The excitation function is usually required to satisfy a monotonic increase and be continuous.

### 2.2 Improved genetic algorithm for network weight learning

Here we discuss the learning method of network weights in neural network model (1). Let us first discuss the problem of determining the weights for a given time assuming \( r, p, q, \) and \( k \). Let the observation data be \( \{ y_i(t), y_1(t), ..., y_r(t), t = 1, ..., n \} \). The sliding window can be used to select learning samples, that is, for time \( t \), the input of model (1) is

\[
x_{(i-1)p+j} = y_i(t - j) \quad i = 1, \Lambda, r \quad j = 0, ..., p - 1
\]

The expected output is
\[ z_i = y_1(t+i) \quad i = 1, \cdots, k \]  

Assuming that the corresponding output when the weight is determined is \( Z_i, i = 1, \cdots, k \), then the square error at this time is

\[ SE(t) = \sum_{i=1}^{k} (\bar{Z}_i - Z_i)^2 \]  

Where \( z_i, i = 1, \cdots, k \) is determined by (5). Therefore, the weight learning problem can be reduced to the following optimization problem:

\[ \min_{\theta, \phi, p} \sum_{t=p+1}^{t \rightarrow 0} SE(t) \]  

Among them

\[
\begin{bmatrix}
    w_{11} & \Lambda & w_{im} \\
    M & M & \\
    w_{q1} & \Lambda & w_{qm}
\end{bmatrix} 
\quad 

\begin{bmatrix}
    v_{11} & \Lambda & v_{1q} \\
    M & M & \\
    v_{k1} & \Lambda & v_{kq}
\end{bmatrix} 
\quad 

\begin{bmatrix}
    \theta_1 \\
    M \\
    \theta_q \\
    M
\end{bmatrix} 
\quad 

\begin{bmatrix}
    \phi_1 \\
    M \\
    \phi_k
\end{bmatrix}
\]  

If the slow change of the structure is taken into account, it can be multiplied by the forgetting factor \( \lambda \), at this time formula (6) can be reduced to

\[ \max_{W \times V, \theta, \phi} f(W, V, \theta, \phi) = -\sum_{t=p}^{n-1} \lambda^{n-t-1} SE(t) \]  

Among them \( 0 < p < 1 \).

Next consider the optimized genetic algorithm. The learning of neural network connection weights has the characteristics of too many parameters. In order to solve the problem of too long encoding caused by the high dimension of variables, we consider improving the genetic algorithm, that is, not binary encoding the variables, but directly using the parallel search mechanism of the genetic algorithm [3]. The algorithm steps are shown in Figure 2.

![Figure 2. Improved genetic algorithm steps](image)

1. Encoding method. It can be formed by cascading each parameter \((W, V, \theta, \phi)\), and its total length is \( r p q + q k + q + k \).

\[ z_i = y_1(t+i) \quad i = 1, \cdots, k \]  

Assuming that the corresponding output when the weight is determined is \( Z_i, i = 1, \cdots, k \), then the square error at this time is

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\quad 

\begin{bmatrix}
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    M & M & \\
    v_{k1} & \Lambda & v_{kq}
\end{bmatrix} 
\quad 

\begin{bmatrix}
    \theta_1 \\
    M \\
    \theta_q \\
    M
\end{bmatrix} 
\quad 

\begin{bmatrix}
    \phi_1 \\
    M \\
    \phi_k
\end{bmatrix}
\]  

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1. Encoding method. It can be formed by cascading each parameter \((W, V, \theta, \phi)\), and its total length is \( r p q + q k + q + k \).
2. Parameter setting. Determine the algorithm parameters, such as population size \( N \), crossover probability \( P_c \), mutation probability \( P_m \), genetic size \( 2d(2d<N) \).

Initial group selection. \( t=0 \), select the initial group \( G_0 = \{g_1, \ldots, g_N\} \).

Suppose the \( t \) generation group \( G_t = \{g_1, \ldots, g_N\} \), calculate and adjust the fitness value as follows:

\[
F_i = f(g_i) - f_{min} + \frac{f_{max} - f_{min}}{N}
\]

(9)

Among them, \( f(g_i) \) represents the function value of equation (10) corresponding to the \( (W,V,\theta,\phi) \) parameter value of \( g_i \). Considering that \( f(*) \) is a negative value, it is necessary to float it appropriately [4].

3. Define the following probability distribution:

\[
P(g_i) = \frac{F_i}{\sum_{i=1}^{N} F_i} \quad i = 1, \ldots, N
\]

(11)

4. Genetic algorithm. \( t=t+1 \), follow the steps below to generate a new group:

2.3. Multi-dimensional and multi-step forecasting nonlinear time series model

Various economic indicators describing the same economic problem are often related to a certain degree, so it is necessary to consider them as a whole. For multi-step forecasting, recursive forecasting is mostly used. Due to modeling errors, this makes the forecasting errors gradually add up. To this end, this article considers the following model [5]. Suppose the prediction has \( r \) indicators, and the prediction is divided into \( k \) steps, the value of the \( i \)-th indicator at time \( t \) is \( y_i(t) \), and the corresponding random error term is \( \varepsilon_i(t) \); the excitation function of the \( j \)-th step prediction of the \( i \)-th indicator is \( f_{ij}(\cdot) \).

\[
f_{ij}(\cdot) = f_{ij}(y_1(t), \ldots, y_1(t-p+1), \ldots, y_r(t), \ldots, y_r(t-p+1))
\]

(12)

\( f_{ij}(\cdot) \) is a nonlinear function and \( p \) being the order. The result of the \( k \)-step prediction of the first indicator starting from time \( t \) corresponds to the equation

\[
\begin{bmatrix}
y_1(t+1) \\
y_1(t+k)
\end{bmatrix} = \begin{bmatrix}
f_{11}(\cdot) \\
f_{1k}(\cdot)
\end{bmatrix} + \begin{bmatrix}
\varepsilon_1(t+1) \\
\varepsilon_1(t+k)
\end{bmatrix}
\]

(13)

The neural network that predicts \( r \) indicators corresponds to the following equation:

\[
\begin{bmatrix}
y_1(t+1) \\ y_r(t+1)
\end{bmatrix} = \begin{bmatrix}
f_{11}(\cdot) & \cdots & f_{1r}(\cdot) \\
f_{r1}(\cdot) & \cdots & f_{rk}(\cdot)
\end{bmatrix} + \begin{bmatrix}
\varepsilon_1(t+1) & \cdots & \varepsilon_r(t+1) \\
\varepsilon_1(t+k) & \cdots & \varepsilon_r(t+k)
\end{bmatrix}
\]

(14)

Obviously, (11) is the first component equation of the above equations.

3. Case analysis

3.1. Sample data

The source of the sample data is 20 ordinary civil construction project valuation examples in a certain city. This paper will include 16 samples in the training set to train the BP neural network. The test set is composed of 4 samples to test the accuracy of the trained BP neural network model. The ANN model of construction project evaluation consists of input layer, hidden layer and output layer [6]. The network structure is shown in Figure 3.
3.2. Determination of Conditional Attribute Set and Decision Attribute Set

In this article, the conditional attribute set C contains 21 attributes, namely engineering type (C1), structure type (C2), single-story height (C3), number of floors (C4), basic type (C5), concrete supply form (C6), pile foundation type (C7), exterior wall decoration (C8), interior wall decoration (C9), masonry engineering (C10), floor engineering (C11), door and window engineering (C12), ceiling decoration (C13), plane combination (C14), equipment engineering (C15), hydropower engineering (C16), beam and column engineering (C17), circulation space (C18), price index (C19), structural area coefficient (C20), decision attribute set D is a single attribute set, namely unilateral cost (D1).

3.3. Model training and simulation

It can be seen from Figure 4 that the convergence speed and accuracy of the hybrid GA-ANN model are significantly improved compared to other network models. It can be seen from Table 1 that the relative error between the model's evaluation results and the real results can basically be controlled within 5%, and both have good prediction effects [7]. However, the relative error of the hybrid GA-ANN model in simulation is smaller. The mixed GA-ANN model has a smaller error range when estimating the construction project cost than other models, and it has a better fit with the actual project cost in the estimation. It can be concluded that the hybrid GA-ANN model is better than other models in terms of predictive effect. The error can be controlled within the range of 2.5%, which is an acceptable range. This model has a significant improvement over the traditional ANN model. Can better estimate the construction cost.

| Table 1. Output results and actual results of the test samples |
|---------------------------------------------------------------|
| Construction project valuation | Absolute error % | Relative error % |
|--------------------------------|------------------|-----------------|
| Actual | ANN | GA-ANN | Actual | ANN | GA-ANN | Actual | ANN | GA-ANN |
| wood 0.0037 | 0.0035 | 0.0038 | 0.0002 | 0.0001 | 5.71 | 2.703 |
| Cement consumption 251.74 | 247.09 | 251.74 | 4.65 | 0 | 1.85 | 0 |
| Cost per square meter 1142.75 | 1185.84 | 1142.75 | -3.09 | 0 | 3.77 | 0 |
| Steel consumption per 100 m2 35.86 | 37.18 | 35.87 | 1.32 | 0.01 | 3.68 | 0.028 |

Figure 3. Flow chart of the hybrid GA-ANN model
4. Conclusion
The GA-ANN model can be used to easily establish the nonlinear relationship between the construction engineering structure and the engineering cost. The model can be trained and tested through training and test samples. Only the construction engineering structure parameters need to be input into the trained neural network during application. In the model, the corresponding project cost can be obtained. This method is very simple, intuitive, accurate and efficient, and has broad application prospects.

References
[1] Tam, C. M., & Tong, T. K. GA-ANN model for optimizing the locations of tower crane and supply points for high-rise public housing construction. Construction Management and Economics, 21(3) (2003) 257-266.
[2] Mahdiani, M. R., & Khamehchi, E. A modified neural network model for predicting the crude oil price. Intellectual Economics, 10(2) (2016) 71-77.
[3] Koopialipoor, M., Armaghani, D. J., Haghighi, M., & Ghaleini, E. N. A neuro-genetic predictive model to approximate overbreak induced by drilling and blasting operation in tunnels. Bulletin of Engineering Geology and the Environment, 78(2) (2019) 981-990.
[4] Armaghani, D. J., Raja, R. S. N. S. B., Faizi, K., & Rashid, A. S. A. Developing a hybrid PSO–ANN model for estimating the ultimate bearing capacity of rock-socketed piles. Neural Computing and Applications, 28(2) (2017) 391-405.
[5] Becker, D., Minsker, B., Greenwald, R., Zhang, Y., Harre, K., Yager, K., ... & Peralta, R. Reducing long - term remedial costs by transport modeling optimization. Groundwater, 44(6) (2006) 864-875.
[6] Bee Hua, G. The state of applications of quantitative analysis techniques to construction economics and management (1983 to 2006). Construction Management and Economics, 26(5) (2008) 485-497.
[7] Liu, L., Moayedi, H., Rashid, A. S. A., Rahman, S. S. A., & Nguyen, H. Optimizing an ANN model with genetic algorithm (GA) predicting load-settlement behaviours of eco-friendly raft-pile foundation (ERP) system. Engineering with Computers, 36(1) (2020) 421-433.