Construction project cost estimation model cost dependent on multi-objective fuzzy optimization calculation

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Abstract: With the development of the social economy, the number and scale of construction projects are also growing. How to control construction project costs has become the key to investment and construction. Based on the multi-objective fuzzy optimization computing, the completed project investment data in the actual project progress is used for empirical analysis of a construction project using the cost prediction model.

1. Introduction
With the development of the social economy, the number and scale of construction projects are also growing [1-2]. How to control construction project costs has become the key to investment and construction. Estimation aims to provide decision support for the cost control of projects, which is mainly shown in two aspects: Firstly, providing services for the decision-making of cost control measures or corrective measures [3-4]. If the prediction results suggest that the investment target will be broken, appropriate corrective measures need to be taken; secondly, adjusting the capital utilization plan [5]. The original investment use plan is prepared according to the planned completion of the project, and it complies with the actual investment. The differences between the investment forecasts of unfinished projects are inevitable. If the differences exceed a specific range, it suggests that the original fund use plan is problematic, and that the fund use plan should be adjusted. Studies by relevant experts and scholars indicate that the factors restricting the development of buildings are: construction cost, construction policy system, construction demand environment, etc., among which construction cost is the primary factor restricting the realization of large-scale construction.

In this paper, based on the multi-objective fuzzy optimization computing, the completed project investment data in the actual project progress is used for empirical analysis of a construction project using the cost prediction model to verify the effectiveness of the proposed cost estimation model.

2. Multi-objective fuzzy optimization algorithm
2.1. Working mechanism
Firstly, determine the input vector of the network and then assign initial values to the connection weights and thresholds of each layer. In the forward transmission of information, sample errors are common. The errors are further transmitted in the reverse direction. During the process, the errors are assigned to each node, and each weight and threshold will be adjusted by calculating the node error,
and so on until the set expected error is reached.

The definition of output layer error:

\[ E = \frac{1}{2} (d - y)^2 = \frac{1}{2} \sum_{k=1}^{p} (d_k - y_k)^2 \] (1)

The error computing definition of the hidden layer and the input layer can be expanded from this.

The weight correction of the output layer node:

\[ V_{j} (u+1) = V_{j} (u) + \eta \delta y_j \] (2)

Threshold correction:

\[ \theta_i (u+1) = \theta_i (u) + \eta \delta_i \] (3)

Weight correction of hidden layer nodes:

\[ W_{ij} (u+1) = W_{ij} (u) + \eta \delta_i x_j \] (4)

Threshold correction:

\[ \theta_i (u+1) = \theta_i (u) + \eta \delta_i \] (5)

Where \( p \) represents the number of samples; \( d_k \) represents the expected value of each node in the output layer; \( y_k \) represents the actual output of each node in the output layer; \( v_{jt} \) and \( w_{ij} \) represent the node weights of the output layer and the hidden layer, respectively; \( u \) represents the number of iterations; \( \theta_i, \theta_j \) represent the node thresholds of the hidden layer and output layer, respectively.

The information transmission is shown in Figure 1.

![Figure 1 Simplified diagram of signal forward and error reverse transmission](image)

Let the input layer input vector be \( X=(x_1, x_2, \ldots, x_n)^T \), the hidden layer output vector be \( T=(t_1, t_2, \ldots, t_m)^T \), the output layer output vector be \( Y=(y_1, y_2, \ldots, y_p)^T \), where \( W \) represents the weight matrix of the input layer-hidden layer; \( V \) represents the weight matrix of the hidden layer-output layer.

The transformation function used in multi-objective fuzzy optimization is often a differentiable monotonic increasing function, such as purelin linear function and sigmoid function. Combined with the analysis of the features of purelin function and sigmoid function, the transfer of neurons in the hidden layer of neural network in this paper The tangent sigmoid function is used, and the purelin function is used for the transmission of the output layer neuron.

The project implementation process can be divided into three stages: preliminary stage, full implementation stage and completion stag completion stage. In the preliminary stage of the project, the construction progress is slow, the implementation stage maintains a relatively fast speed, and the completion stage of the project tends to be flat. This phased characteristic makes the investment also present a phased law, and the corresponding cumulative completed investment is distributed according to the “S”-shaped curve, which essentially conforms to the exponential distribution law.

The GM(1,1) gray model is an exponential model. Firstly, the curve is relatively flat, slowly begins to steep, and continues to grow at such a rate. Its distribution law is consistent with the early and mid-term laws of investment changes. Hence, the GM(1,1) gray model can be used to predict the next few phases of the unfinished project cost after the unfinished project prediction time point, especially the unfinished project cost in the mid-stage where the prediction of the unfinished project cost in the later period is not suitable for predicting the cost of all unfinished projects.

2.2. Predictive model

In the later stage of project implementation, a simple and feasible model can be adopted to predict the
cost of all unfinished projects.

In particular, in the middle and later stages of the implementation phase, the project situation is clearer, when the cost of all unfinished projects can be predicted by a simpler mathematical model, considering the influence of changes in local key factors on the project cost and the influence of global factors. The influence of changes on the project cost. Take a contract project as an example. The final project cost of the contract project predicted at time $t$ is composed of three parts below:

- Contract price in the original plan
- Incremental influence of local key factors on project cost
- Incremental influence of global factors on project cost

The model can be expressed by the following mathematical equation:

$$C_t = C_0 + \Delta C + (C_0 - C_{\alpha} + \Delta C_1)$$

\[
\begin{align*}
\alpha_0 + \alpha_1 A_0 + \alpha_2 B_0 + \alpha_3 C_0 + \alpha_4 D_0 + \cdots \\
\Delta C = \Delta C_1 + \Delta C_2
\end{align*}
\]

\[
\Delta C_2 = \sum_{j=1}^{n} (P_j Q_j - P_i Q_j) + \sum_{j=1}^{n} P_j Q_j
\]

Where:
- $C_t$-predict the final engineering cost of the contract project at time $t$
- $C_0$-Planned contract price
- $\Delta C_1$- deviation of the cumulative project cost of the actual completed project at the time of prediction
- $\Delta C_2$-prediction deviation of the influence of local factors on the cost of all unfinished projects during prediction: $Q_0$ represents the predicted unit price of the key items in the contract at time $t$, $P_0$ represents the predicted engineering volume of the key items in the contract at time $t$, and $Q_i$ represents the contract item. The original planned unit price of the key item in the middle, $P_i$ represents the original planned engineering quantity of the key item in the contract project, and $P_j Q_j$ represents the estimated new project cost for all unfinished projects at the forecast time.

(C0-Cat+ΔCt) is determined according to the proportion of the total price, no more than 5 shares per share. $\alpha_0+\alpha_1+\alpha_2+\alpha_3+\alpha_4+\cdots=1$, the number of $\alpha$ is determined according to the engineering grid index;

$A_0, B_0, C_0, D_0$-base period price index of various expenses corresponding to $\alpha_1, \alpha_2, \alpha_3, \alpha_4$...

3. Construction cost estimation

3.1. Determination of engineering similarity

Fuzzy pattern recognition refers to the determination and analysis of some unclear things, which includes direct and indirect methods of identification. Given that the object to be estimated in this article is a fuzzy recognition problem, the indirect fuzzy pattern recognition can be used for engineering projects. The similarity is determined.

3.2. Indirect fuzzy pattern recognition

Definition of indirect fuzzy pattern recognition:

Let $A_1, A_2, \ldots, A_n$ be all fuzzy modes on the universe $U$, $B$ be an object to be evaluated on $F(U)$, $\alpha$ be a certain fuzzy closeness on $F(U)$. If there is $\alpha(B, A_i) = \max(\alpha(B, A_1), \alpha(B, A_2), \ldots, \alpha(B, A_n))$, $B$ is referred to as the fuzzy mode on $A_n$.

There are multiple types of fuzzy closeness mentioned in the definition. The commonly used ones include Euclid closeness, Chebyshev closeness, maximum and minimum closeness, arithmetic mean minimum closeness, Hamming closeness, etc. Since closeness reflects the similarity of fuzzy sets, it can describe the relationship between the same subset and different subsets between the sets properly.
3.3. Selection of project samples

Give the features of multi-objective fuzzy optimization, to ensure the estimation accuracy, the number of input vectors of the network must be large enough, so this paper selected 28 project features and structural features of the built green building cost data from the cost consulting agency.

(1) Screening of green building cost estimation index indexes

When estimating the cost of green building projects, the various index indexes used to estimate the cost have different effects on the cost. Hence, the weight of each index in the cost should be analyzed and compared. The 13 items selected in this article Among the index indexes, the number of floors, the height of the floor, the type of water-saving measures, the intelligentization of buildings, the project category and the cost index are all non-consumption index indexes of physical materials, so they are not taken into consideration. Other physical material consumption index indexes to be included in the project feature fuzzy set are as follows:

\[ U = \{ \text{type of foundation, type of doors and windows, structural form, exterior wall decoration, interior wall decoration, wall material, floor decoration} \} \]

(2) Construct the membership function of the sample project

Common methods for constructing membership functions include: binary contrast ranking method, fuzzy statistics method, Delphi method, etc. The membership function is generally symmetrical and balanced, and has unimodal features. According to the construction method of the membership function in some documents combined with the specific situation of the project in this paper, the binary comparison sorting method is adopted. The method is described as follows:

Let the domain be \( U = \{ u_1, u_2, \ldots, u_m \} \), \( A \in F(U) \). The attributes of each element are compared to determine the attribute value \( n_{ij} \) of each element in \( A \) and the weight assignment value \( \alpha_i \) for \( A \) (set each element in \( A \) weight values in \( \alpha_1, \alpha_2, \ldots, \alpha_m \), then \( \sum_{i=1}^{m} \alpha_i = 1, \alpha_i \in (0,1) \)), then the membership function of the sample project \( A_1 \) can be obtained as \( A_1(u_i) = \{ \alpha_i s_{ij} \} \), where \( i=1,2, \ldots \); \( j=1,2, \ldots \); the membership functions of other sample projects and projects to be evaluated are similarly available.

(3) Selection of sample projects

Sample projects are selected based on the fuzzy closeness. Before calculating the fuzzy closeness, the attributes and weights of the sample project, and the project to be evaluated must be assigned. After interviews with professional costing personnel, the samples are consolidated, as shown in Tables 1 and 2.

| Characteristic index | Base type | Doors and Windows type | Structure type | Interior decoration | Exterior wall decoration | Wall materials | Floor decoration |
|---------------------|-----------|------------------------|----------------|---------------------|-------------------------|---------------|-----------------|
| Weight              | 0.1       | 0.15                   | 0.3            | 0.15                | 0.1                     | 0.11          | 0.09            |

| Project index indexes | Assignment |
|-----------------------|-------------|
| Types of foundations  |             |
| Types of doors and windows |             |
| Structural styles  |             |
| Exterior, interior wall |             |
The assignment data in the above table are used to the membership functions of the sample project and the project to be assessed, the Zadeh notation in fuzzy mathematics can represent the fuzzy set of the project to be evaluated as follows:

$$U_B = \frac{0.1}{u_1} + \frac{0.15}{u_2} + \frac{0.24}{u_3} + \frac{0.19}{u_4} + \frac{0.088}{u_5} + \frac{0.072}{u_6}$$

Similarly, a fuzzy set of each sample project can be obtained.

In this paper, the arithmetic average minimum closeness is used to calculate the similarity between the sample project and the project to be estimated. The project with the calculated closeness greater than 0.7 is used as the sample project of the project to be estimated. Hence, 21 projects are selected from 28 sample projects with high similarity to the project to be estimated in this paper. Moreover, 3 of the 21 sample projects are randomly selected as test samples, and the rest are training samples.

### 3.4. Construction cost estimation of green building

The features of multi-objective fuzzy optimization are combined to reduce the number of hidden layer neurons, the 13 index indexes mentioned above that affect the estimation should be further processed before they can be used as the input vector of the neural network. The entity that affects the engineering cost estimation Material consumption index indexes can be further divided into basic engineering index indexes (basic type), decoration engineering index indexes (external wall decoration, interior wall decoration, door and window type, floor decoration) and main engineering index indexes (structure type, wall materials) according to categories. The value of each of these three types of index indexes is the sum of the product of the attribute value of each feature index and its weight value. The other 6 types of physical material non-consumption index indexes are directly used as the input vector of the network. Hence, the input of the neural network vectors are basic engineering, decoration engineering, main engineering, number of floors, floor height, type of water-saving measures, building intelligence, engineering category, and cost coefficient. All input vectors are normalized.

### 4. Discussion

Given the issue of hidden layer neurons, the “trial and error method” is used in this paper to determine the final number of hidden layer neurons. Firstly, the initial value for the number of hidden layer neurons is set to 3. Subsequently, the network program is trained. The number of hidden layer neurons is increased gradually (the maximum is 12), and the same sample set is used for training. As the result, when the number of hidden layer neurons is 8, the average error value of the network reaches the minimum, so this article selects The number of hidden layer neurons is 8. Matlab software and 18 sample projects are used to train the network program. The final test sample results are shown in Table 3 below.

| Test sample no. | Actual value/wan | Estimated value/wan | Relative error value/% |
|-----------------|------------------|---------------------|------------------------|
| Eight           | 1024             | 1056                | 3.41                   |
| Twelve          | 966              | 997                 | 2.92                   |
| Sixteen         | 852              | 824                 | 3.63                   |
Fuzzy mathematics are combined with multi-objective optimization theory to obtain sufficient accuracy in estimating construction costs, which is of certain practical value for cost control.

5. Conclusions
In this paper, based on the multi-objective fuzzy optimization computing, the completed project investment data in the actual project progress is used for empirical analysis of a construction project using the cost prediction model to verify the effectiveness of the proposed cost estimation model. The estimation of construction project costs can provide data for the decision of construction company and project management departments to develop cost plans, which is conducive to identifying problems timely, analyzing deviations, adjusting cost plans, correcting errors, and pinpointing weak links in the cost management of construction projects, taking measures to tap the rectification potential, reduce the cost, improve economic efficiency, and enhance corporate competitiveness in domestic and foreign markets.

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