Comparison of Topsis Comprehensive Evaluation System and Computer BP Neural Network Simulation

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Abstract. In view of the fact that the subjective determination method will be affected by natural and man-made factors, it has high uncertainty. In order to further improve the accuracy of the algorithm, considering the comprehensive effect of various factors has become the key to solving the problem. Therefore, the paper first uses the analytic hierarchy process to initially determine the weights, uses the fuzzy inference model to make preliminary predictions based on the similarity of the impact factor matrix, and then we use the Topsis-fuzzy comprehensive evaluation model to identify the impact factors, and screen out the reasonable predictors for the second time prediction. Finally, we use an example to test the effect of the fuzzy inference model based on the Topsis-fuzzy comprehensive evaluation model factor identification, and compare it with the BP model of the fuzzy optimization neural network for ice forecasting. The results show that the TOPSIS-fuzzy comprehensive evaluation model factor identification basis the above fuzzy inference model has higher prediction accuracy and better effect.

1. Introduction

With the continuous development of simulation technology and the gradual deepening of people's understanding of the application value of simulation technology, its application fields are becoming more and more extensive, and the requirements for the accuracy and credibility of simulation are getting higher and higher. Whether the simulation system is credible will directly affect a series of applications or decision-making processes based on the simulation results [1]. At the same time, the simulation system is becoming more and more complicated, making its credibility assessment more and more difficult.

Generally speaking, the credibility evaluation of a simulation system can be transformed into a multi-index, multi-factor comprehensive evaluation problem. In the evaluation process, it is necessary to establish an evaluation index system and determine the weight of each index. The weight of the indicator reflects the relative importance of each indicator, and also reflects the position and role of each indicator in the system credibility. The determination of the indicator weight is related to the reliability and validity of the evaluation result.

Fuzzy comprehensive evaluation is a commonly used method for evaluating the credibility of simulation systems. It uses experts to determine the fuzzy comprehensive evaluation matrix from the index set to the evaluation set, then uses the expert determination method or the analytic hierarchy process to give the weight information of each index, and then uses the fuzzy synthesis operation to
obtain the final comprehensive evaluation result. However, the weight distribution of indicators will be
affected by the personal preferences and expectations of experts, and there is no relatively clear criterion
for the choice of fuzzy synthesis operation, so it is easy to cause the results of fuzzy comprehensive
evaluation to be invalid or inaccurate [2].

Therefore, in view of the limitations of traditional fuzzy comprehensive evaluation methods in
credibility evaluation, the paper proposes a simulation credibility evaluation method based on improved
fuzzy comprehensive evaluation. Aiming at the tree-type evaluation index system commonly used in
credibility evaluation, the fuzzy comprehensive evaluation matrix is used to determine the weight of
each level of the index system based on the weighted average deviation of the minimum membership
degree, reducing the subjectivity of the traditional method to determine the weight; in the fuzzy synthesis
link , Use the weighted average deviation of the membership degree to obtain the comprehensive
evaluation vector to avoid the inaccuracy of the evaluation result caused by the improper selection of
the fuzzy synthesis operation; through the credibility evaluation example, the rationality and feasibility
of the proposed method are verified.

2. Analytic hierarchy process weight determination

2.1. Constructing an extension judgment matrix

Use the analytic hierarchy process to structure its hierarchical structure. At the same time, for the factors
in the k-1 layer, all the factors \( n \) related to the next level are listed [3]. After the connection between
the two, the extension interval number is used to define its relative importance. And then construct an
extension judgment matrix \( A \). Among them, the matrix \( A = \left( a_{ij} \right)_{n \times n} \) satisfies \( \forall i, j = 1,2,...,n \) and
covers the element \( a_{ij} = \left( a^+_{ij}, a^-_{ij} \right) \), which is an extension interval number. Assumption:
\( a_{ij} = \left( a^+_{ij}, a^-_{ij} \right) \)
and \( \frac{l}{g} \leq a^-_{ij} \leq a^+_{ij} \leq 9 \), \( a_{ij} = \frac{1}{a_{ji}} \). Then there is an extension judgment matrix \( A = \left( a_{ij} \right)_{n \times n} \) which is
opposite to each other, then there is

\[
 a_{ii} = 1, a_{ji} = a^+_{ij} = \left( \frac{1}{a_{ij}}, \frac{1}{a^-_{ij}} \right), i, j = 1,2,3...,n
\]  

(1)

2.2. Extension judgment matrix and weight vector determination

We assume that \( a'_{ij} = \left( a^+_{ij}, a^-_{ij} \right) \), \( i, j = 1,2,3...,n \); \( t=1,2,3...,T \) represents the number of extension
intervals established by the t-th expert opinion. There is a formula

\[
 A = \frac{1}{T} \bigotimes \left( a^+_{ij} + a^-_{ij} + a^+_{ij} + ... + a^+_{ij} \right)
\]  

(2)

We can obtain the calculation steps of the weight vector of the k comprehensive extension interval
number judgment inverse matrix \( A = \left( A^-, A^+ \right) \) as follows:

1. Obtain the normalized eigenvector \( X^- , X^+ \) with the positive component corresponding to the
maximum eigenvalue of \( A^-, A^+ \).

2. There is a formula from \( A^- = \left( a^+_{ij} \right)_{n \times n} , A^+ = \left( a^-_{ij} \right)_{n \times n} \) :

\[
 k = \sqrt{\frac{\sum_{j=1}^{n} \frac{1}{a_{ij}} \sum_{i=1}^{n} a_{ij}}{m}}, m = \sqrt{\frac{\sum_{j=1}^{n} \frac{1}{a_{ij}}}{\sum_{i=1}^{n} a_{ij}}}
\]  

(3)
(3) Get the weight vector

\[ S^k = (S^k_1, S^k_2, S^k_3, ..., S^k_n) \]  

(4)

2.3. Single-sort weight vector solution

Let \( a = (a^-, a^+) \), \( b = (b^-, b^+) \) be two predetermined extension interval numbers. If there is \( V(a \geq b) \), then there are formulas:

\[ V(a \geq b) = \frac{2(a^+-b^-)}{(b^+ - b^-) + (a^+ - a^-)} \]  

(5)

\[ b^- < a^+ \), \( V(a \geq b) > 0 \), means the degree of probability of \( (a \geq b) \). \( b^+ > a^+ \), \( V(a \geq b) < 0 \), means the probability degree that \( (a \geq b) \) is unlikely to occur; \( b^+ = a^+ \), \( V(a \geq b) = 0 \). According to the above formula: \( V(S^k_i \geq S^k_j) (i=1,2,3...n_k, i \neq j) \). Assumption: \( V(S^k_i \geq S^k_j) \geq 0 \), \( \forall i = 1,2,..,n_k, i \neq j \), then:

\[ P^h_{j|i} = 1, P^h_k = V(S^k_i \geq S^k_j), (i=1,2,3...n_k, i \neq j) \]  

(6)

\( P^h_{j|i} \) represents the single order of the \( i \) element on the \( k \) level relative to the \( h \) factor on the \( k-1 \) level. After normalization, we get: \( P^h_k = (P^h_{1|i}, P^h_{2|i}, P^h_{3|i}, ..., P^h_{n|i}) \). The above formula represents the single order weight vector of each element in the \( k \) level to the \( h \) factor in the \( k-1 \) level. After combing, we can get the weight calculation process of the extension analytic hierarchy process as shown in the figure below.

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**The set of candidate services** \( S = \{s_1, s_2, ..., s_M\} \)

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**Figure 1.** Extensible Analytic Hierarchy Process flow chart
2.4. Static weight of the state assessment model

The extension evaluation method is generally limited to the first-level evaluation, but because the state parameter information is more complicated, it is necessary to classify the information to establish the extension evaluation method [4]. We use \( X_i (1 \leq i \leq H) \) to represent and evaluate indicators, and there are \( n_j (1 \leq j \leq H) \) secondary indicators \( X_{ij} \) and \( n_k (1 \leq k \leq n) \) three-level indicators \( X_{ijk} \) under the secondary indicator \( X_{ij} \). The extension analytic hierarchy process used in the thesis determines the static weight.

3. Dynamic empowerment

3.1. Constructing a matrix

In a model with M Zhuangtian, including n evaluation index systems, we use the principle of qualitative and quantitative combination to obtain the evaluation matrix \( D = \left[ d_{ik} \right]_{m \times n} \). We define \( d_{ik} \) as the assignment of the \( k \) evaluation index under the \( i \) state model.

3.2. Normalization

According to the state evaluation indicator system in Chapter 2, it can be found that the values corresponding to each indicator are different, and direct comparison will bring certain difficulties to the calculation. Therefore, in the comprehensive quantitative evaluation, we generally need to use standardized processing methods to normalize the state evaluation index data and transform it into dimensionless data, that is, transform the matrix \( D = \left[ d_{ik} \right]_{m \times n} \) into a standardized matrix \( Q = \left[ q_{ik} \right]_{m \times n} \) after the standardized processing [5]. Generally, the information corresponding to the evaluation index scoring system falls into three categories: the larger the better, the smaller the better, and the better the median value. Different linear standards are used to transform different index systems.

1) The bigger the better:

\[
q_{ik} = \frac{d_{ik} - d_{k\ min}}{d_{k\ max} - d_{k\ min}} \quad (i = 1, 2, \ldots, m; k = 1, 2, \ldots, n) \tag{7}
\]

2) The smaller the better:

\[
q_{ik} = \frac{d_{k\ min} - d_{ik}}{d_{k\ max} - d_{k\ min}} \quad (i = 1, 2, \ldots, m; k = 1, 2, \ldots, n) \tag{8}
\]

3) The better the median value:

\[
q_{ik} = \frac{1 - \left| d_{ik} - d^*_k \right|}{\max_{k=1,2,\ldots,n} \left| d_{ik} - d^*_k \right|} \quad (i = 1, 2, \ldots, m; k = 1, 2, \ldots, n) \tag{9}
\]

Among them: \( d_{ik} \) represents the k index value \( d_{k\ max} \), \( d_{k\ max} \) of the i state, represents the maximum value of the k index of each state, and the minimum value \( d^*_k \) represents the ideal value of the k index. According to formula 7.9, the matrix \( D = \left[ d_{ik} \right]_{m \times n} \) is standardized and transformed into a standardized matrix \( Q = \left[ q_{ik} \right]_{m \times n} \).
3.3. Definition of the k index entropy

\[ H_k = -K \sum_{i=1}^{m} f_{ik} \ln f_{ik} \quad (k = 1, 2, ..., n) \]  

(10)

Among them: \( K = 1 / \ln m \), \( f_{ik} = q_{ik} / \sum_{i=1}^{m} q_{ik} \). Assume that \( f_{ik} = 0 \) has \( f_{ik} \ln f_{ik} = 0 \).

3.4. Calculating the entropy weight \( \varepsilon_i \)

According to the analysis of the nature of entropy, the entropy value of the relative importance of each index is defined, as follows:

\[ \varepsilon_i = \frac{1 - H_i}{n - \sum_{i=1}^{n} H_i} \quad (i = 1, 2, ..., n) \]  

(11)

According to the entropy function defined by the above formula, the relevant properties of the entropy weight method can be obtained as follows: First, if the value of a certain index evaluated remains unchanged, the entropy value is 1, the entropy weight \( \varepsilon_i = 0 \), this index does not need to be considered inside. Second, if there is a large difference in the value of all evaluation objects, the corresponding entropy value is small, and the entropy weight \( \varepsilon_i \) has a large value, indicating that this indicator plays a very important role in this state, and it can be Decision makers provide relatively rich information, and focus on application in state evaluation. Third, the entropy value of the evaluation index is inversely proportional to the entropy weight [6]. The larger the entropy value, the smaller the value of the entropy weight \( \varepsilon_i \), indicating that the status of the index is smaller, and the following equation is also satisfied.

\[ j \leq \omega_i \leq 1 \]

(12)

Fourth, after the evaluation object is determined, the entropy weight value generally needs to be adjusted and increased or decreased according to the size of the entropy weight in order to make the evaluation more accurate and reliable. The entropy weight helps to determine the accuracy of the indicator value more accurately.

4. Topsis- Fuzzy Comprehensive Evaluation Model

In practical applications, it is unwilling to choose a single subjective weight determination or objective weight assignment, because a single use cannot obtain satisfactory results. It is a relatively common way for us to combine subjective and objective empowerment. This method can calculate various indicators and ask experts to give relatively authoritative subjective weights, and use certain formulas to combine the two weights. Get the Topsis-fuzzy comprehensive evaluation model. For this reason, we combine objective information with subjective judgments to reflect the true weight of each indicator [7]. The method that the paper adopts both subjective and objective weights is the analytic hierarchy process combined with the entropy weight method to determine the Topsis-fuzzy comprehensive evaluation model. The combined weighting expression is as follows:

\[ \mu_i = \frac{\varepsilon_i \omega_i}{\sum_{j=1}^{n} \varepsilon_j \omega_j} \]  

(13)

Among them, \( \mu_i \) represents the Topsis-fuzzy comprehensive evaluation model obtained through weighting. \( \omega_i \) represents the subjective weight obtained by the analytic hierarchy process. \( \varepsilon_i \) represents
the objective weight obtained by using entropy information. However, the Topsis-fuzzy comprehensive evaluation model obtained in the above way has a "multiplier" effect, which means that the larger the weight is larger, and the smaller the weight is smaller. This method has certain drawbacks. For this reason, in this time the weighting method given in the paper is a linear combination weighting method. The expression is as follows:

$$\mu_i = \alpha \omega_i + (1-\alpha) \omega_i$$

(14)

(1) $\alpha = 0$, the Topsis-fuzzy comprehensive evaluation model uses objective weights, (2) $\alpha = 1$, the Topsis-fuzzy comprehensive evaluation model uses subjective weights. This expression fully absorbs the advantages of the entropy weight method and the analytic hierarchy process. When subjective weights need to be used, expert experience and historical data are used as the main source of weight coefficients to eliminate the influence of objective weights; when objective weights need to be used, use the weight of entropy method is used as the main source of weight coefficient to eliminate the influence of subjective weight.

5. Example simulation

This article takes a semi-physical simulation system as a background, and uses an improved fuzzy comprehensive evaluation method to evaluate its credibility. The judgment matrix is established by the scoring method and the relative error method, and we use the TOPSIS-fuzzy comprehensive evaluation method to make the evaluation. The evaluation results are shown in Table 1.

| Program | Total points | Relative error 1 (%) | Relative error 2 (%) | Relative error 3 (%) | Relative error 4 (%) | Relative error 5 (%) |
|---------|--------------|-----------------------|----------------------|----------------------|----------------------|----------------------|
| 1       | 3            | 16.67                 | 5                    | 11.36                | 2.5                  | 2.33                 |
| 2       | 4            | 14.29                 | 5                    | 2.27                 | 2.5                  | 2.33                 |
| 3       | 2            | 7.14                  | 5                    | 4.35                 | 10                   | 6.98                 |
| 4       | 4            | 0                     | 5                    | 11.36                | 5                    | 2.33                 |
| 5       | 3            | 16.67                 | 2.5                  | 2.27                 | 7.5                  | 2.33                 |
| 6       | 5            | 0                     | 5                    | 2.27                 | 5                    | 2.33                 |
| 7       | 4            | 11.9                  | 2.5                  | 2.27                 | 2.5                  | 2.33                 |
| 8       | 3            | 14.29                 | 10                   | 2.27                 | 5                    | 2.33                 |

This paper uses TOPSIS-fuzzy comprehensive evaluation method to screen and identify influencing factors, and uses fuzzy inference method to predict a certain semi-physical simulation system [8]. Compared with the literature using fuzzy optimization neural network BP model to compare the results, it is shown that based on TOPSIS- Fuzzy comprehensive evaluation method the errors of the five prediction values of the fuzzy inference model identified by the factor identification of a semi-physical simulation system are all within the allowable error range, and the relative error is small. The accuracy of the prediction results is much better than the fuzzy optimization neural network model. The comparison results are shown in the table. 2.

| Serial number | Years  | Measured value | Fuzzy inference prediction interval | Forecast error (%) | Fuzzy Optimal Neural Network Forecast Value | Forecast error (%) |
|---------------|--------|----------------|------------------------------------|--------------------|--------------------------------------------|--------------------|
| 1             | 2016-2017 | 42             | [39.6, 44.4]                       | 0                  | 35                                         | 16.6               |
| 2             | 2017-2018 | 40             | [39.6, 44.4]                       | 5                  | 39                                         | 2.5                |
| 3             | 2018-2019 | 44             | [40.45, 45.55]                     | 2.27               | 42                                         | 4.55               |
| 4             | 2019-2020 | 40             | [39.6, 44.4]                       | 5                  | 46                                         | 15                 |
| 5             | 2020-2021 | 43             | [41.3, 46.7]                       | 2.33               | 44                                         | 2.3                |
6. Conclusion
The fuzzy inference model proposed in this paper based on the TOPSIS-fuzzy comprehensive evaluation method for the identification of a semi-physical simulation system can use reasonable factors to establish a model based on the identification of predictive factors to predict the duration of the Kaifeng River on the ice, and the fuzzy optimization neural network BP compared with the model, the accuracy has been greatly improved.

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