Research on Group Risk Security Decision Based on BP Neural Network Algorithm

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Abstract. Aiming at the uncertainty and diversity characteristics of risk assessment objects in group decision making, this paper proposes an information security risk assessment method based on BP neural algorithm. The paper gives a detailed risk assessment process and evaluation method for group decision-making security. The established group decision-making risk assessment system adopts the BP neural network method, which is a non-linear method, without obvious subjective components and human factors, making the evaluation results more effective and more objective. The example shows that the calculation results are close to the success story results.

1. Introduction

Multi-attribute group decision making has a wide range of theoretical and practical applications in many fields such as engineering design, economy, management and military. Background Group decision-making for project risk assessment belongs to the multi-attribute group decision-making process, and the various benefits of participation in decision-making in construction project risk assessment Relevant groups, according to their own interests, professional level, knowledge, experience and comprehensive ability, give their own evaluation of the pros and cons of each attribute of the candidate program. Finally, the experts get the comprehensive synthesis of each program through the multi-attribute group decision-making process. Attribute value, evaluation of program group or preference multi-attribute group decision-making process There are conflicts caused by different decision-makers due to differences in target preferences. The key to conflict resolution is to coordinate the satisfaction of decision makers. In conflict-oriented multi-objective group decision-making model Among them, decision-makers with certain conflicts of interest are set to submit their respective satisfactory decisions to the arbitrators, which constitutes an arbitration situation involving three parties. The two-stage planning and pattern recognition method are used to obtain the ideal solution closest to the arbitration solution. Satisfactory plan, two-stage planning and conflict pattern identification Experience more tedious calculations.

In the actual decision-making process, due to the abstraction of the concept of each attribute of the scheme, the cognitive limitations of the decision makers themselves and the complexity of the decision-making background, the authoritative differences in the decision-making individuals involved in the decision-making are also difficult to quantify, so the fuzzy number is introduced into the scheme. The evaluation of the indicator value, through the fuzzy operation based on the fuzzy mathematical theory to make scientific decisions, will be more in line with the actual decision-making. Many
scholars have discussed the fuzzy weight determination and fuzzy preference aggregation, which has a considerable research basis. This paper uses a combination of qualitative and quantitative methods to evaluate the risk level of group decision-making. The application of BP neural network overcomes the subjectivity of evaluation.

2. Risk assessment process

The process of risk assessment is generally: (1) Identify group decisions and their value. (2) Identify potential threats to the system. (3) Identify the weak points of the decision result for each threat. These weak points refer to weaknesses in the system that can be exploited by threats, and they form a “threat/weakness” pair. (4) Confirm the safety control measures that have been taken. (5) Determine the likelihood of a particular threat event occurring. (6) Determine the consequences of the risk on the system. (7) Establish risk measurement methods and risk factor rating principles to determine the level of each risk factor. (8) Use neural network technology to determine the risk level of the entire system, as shown in Figure 1 [1].

![Fig. 1 Risk assessment process](image)

3. BP neural network algorithm description

There are many algorithms for clustering vectors, such as K-means, fuzzy sets, neural network methods, and so on. We use BP neural network for clustering. Let's briefly introduce the BP network model. BP's SOFM model (i.e., self-organizing feature mapping model) is a neural network model commonly used for clustering. The network structure consists of two layers: the input layer and the BP layer (output layer). The two layers are fully connected, each input layer neuron has a feedforward connection with each output layer neuron, and there is a lateral connection between the output layer neurons [2].

3.1. Introduction to BP Neural Network

The structure of the BP network is shown in Figure 1. It is a fully connected network consisting of an input layer, a hidden layer, a rule base, and an output layer. The number of neurons in the output layer depends on the specific problem. For simplicity, only one output neuron is shown in the figure, and the network can be easily extended into a network of multi-output neurons.
The input data is the number between [0, 1]. The size of the input vectors \(X = x_1, x_2, \ldots, x_N\), \(N\) is determined by the specific problem. Like the general neural network, the number of hidden layer neurons \(H\) is equal to the number of training samples.

The weight of each hidden layer neuron \(i = 1, 2, \ldots, N\) is recorded as vector \(w_i = (w_{i1}, w_{i2}, \ldots, w_{iN})\). \(w_{ij}\) represents the connection weight of the component \(x_j\) in the input vector to the \(i\)-th hidden layer neuron.

![Fig. 2 BP neural network structure.](image)

For each hidden layer neuron \(i\), the Euclidean distance \(d_i\) between the test vector \(X\) and its weight vector \(w_i\) is first calculated. \(r_i\) is the generalized radius of the hidden layer neuron \(i\), and \(d_i\) and \(r_i\) form the input of the activation function \(F\) to calculate the output \(l_i\) of the hidden layer neuron \(i\). As shown in Figure 2, the outputs of the individual hidden layer neurons together form the distance vector \(L = (l_1, l_2, \ldots, l_H)\), which can be used to measure the similarity between the test vector and each training sample[3].

In the neural network, \(r\) is applied to the whole neural network, and each hidden layer neuron in the FCC neural network has its own \(r\), which ensures that the generalization space of each training vector does not overlap, and each hidden layer neuron training. The sample has a generalized space centered on \(w\) and \(r\) is the generalized radius. If the distance between the test vector \(X\) and \(w\) is less than or equal to \(r\), the training samples corresponding to the visual \(X\) and \(w\) are indistinguishable and can be classified into the class represented by the training sample.

The rule base makes the BP neural network more general than the neural network. It consists of an IF - THEN set, and the distance vector \(L\) generates a membership vector \(\mu = (\mu_1, \mu_2, \ldots, \mu_H)\) about the class to which the test vector belongs to each training sample by the IF - THEN rule. The output \(y = \sum_{i=1}^{H} \mu_i\) of the BP neural network can be obtained by the weights \(\mu = (\mu_1, \mu_2, \ldots, \mu_H)\) and \(\mu\) of the output layer.

The role of the rule base is to determine the fuzzy membership of the test vector \(X\). However, in a general neural network, for a certain type of test sample, it belongs to it or does not belong to it. In short, the membership degree of the test vector in the general network is not 0 or 1. However, the value of the membership in the BP neural network can take any value in the [0, 1] interval.
3.2. **BP neural network algorithm flow**

The BP neural network training process consists of two steps:

Firstly, the weights of the input layer and the output layer are determined by the input/output of the training samples. \( w_{ij} \) is the connection weight from the input neuron \( i \) to the hidden layer neuron \( j \). When the \( j \)-th training sample is submitted to the network, \( x_{ij} \) is the input of the \( i \)-th input neuron of the training sample, \( x_{ij} = 1, 2, ..., N, j = 1, 2, ..., H \). The weight of the output layer, \( \mu_i \), is equal to the output \( y_i \cdot \mu_i = 1, 2, ..., N \) of the training sample.

Secondly, the training process determines the generalization radius of each hidden layer of neurons. Let \( d_{\text{min}} \) be the minimum distance from the training vector \( i \) to the non-zero distance of the other training vectors \( j (j \neq i) \), then the generalized radius \( r = d_{\text{min}} \) of the \( i \)-th hidden layer neurons, which ensures the generalization of the hidden layer neurons \( i \). The space does not overlap with the generalized space of other hidden layer neurons[4].

3.3. **Generalization of fuzzy membership**

After completing the training of the BP network, the BP neural network can be deployed and deployed. Enter the test vector to get the distance vector \( L = (l_1, l_2, ..., l_H) \) of the hidden layer, and measure the similarity between the test vector and the trained vector by \( L \). The rule base acts on the distance vector \( L \), generates a membership vector \( \mu = (\mu_1, \mu_2, ..., \mu_H) \) according to the 1NN or kNN algorithm, and produces an output \( y = \sum_{i=1}^{H} \mu_i \mu_i \) using the output layer weights \( u \), \( \mu = (\mu_1, \mu_2, ..., \mu_H) \) and \( \mu \).

4. **Example analysis**

4.1. **Application of Group Decision Risk Judgment Based on BP Neural Network Algorithm**

Step1: According to the problem change in reality and environment, this paper will make certain adjustment on step1. The original document required the expert reconstructed judgment matrix when expert matrix cannot reach the consistency, on the contrary this paper argue that there are various difficulties exist in real practice for reconstructing judgment matrix. The paper claim that the expert data with inconsistency or less consistent could be ignored directly and to simplify the problem, as to the expert judgment matrix formed by evaluating the importance of index system \( G = (G_1, G_2, G_3, G_4, G_5, G_6, G_7) \), on the condition that it is complied with the consistency, and in accordance with the consistent ratio CR sorted from small to large, the top 5 expert judgment matrix is listed as follows:

\[
A_i = \begin{bmatrix}
1 & 2 & 1/2 & 5 & 6 & 6 & 1/2 \\
1/2 & 1 & 1/4 & 3 & 5 & 6 & 1/2 \\
2 & 4 & 1 & 6 & 7 & 8 & 2 \\
1/5 & 1/3 & 1/6 & 1 & 3 & 4 & 1/3 \\
1/6 & 1/5 & 1/7 & 1/3 & 1 & 2 & 1/6 \\
1/6 & 1/6 & 1/8 & 1/4 & 1/2 & 1 & 1/7 \\
2 & 2 & 1/2 & 3 & 6 & 7 & 1
\end{bmatrix}
\]

\[
A_j = \begin{bmatrix}
1 & 2 & 1/2 & 5 & 6 & 7 & 1/2 \\
1/2 & 1 & 1/4 & 2 & 3 & 4 & 1/4 \\
2 & 4 & 1 & 6 & 7 & 9 & 2 \\
1/5 & 1/2 & 1/6 & 1 & 3 & 5 & 1/3 \\
1/6 & 1/3 & 1/7 & 1/3 & 1 & 2 & 1/5 \\
1/7 & 1/4 & 1/9 & 1/5 & 1/3 & 1 & 1/8 \\
2 & 4 & 1/2 & 3 & 5 & 8 & 1
\end{bmatrix}
\]
After calculating, the consistency ratios are: (0.041, 0.045, 0.047, 0.048, 0.050).  

Step2: Grade deviation matrix E is established as above.

Step3: Choosing $e_{ij}^*$

Based on Figure 3, selecting the corresponding elements from the judgment matrix $A_1$-$A_5$ is:

$$a_{i2}^* = 12/5, a_{i3}^* = 7/15, a_{i4}^* = 11/5, a_{i5}^* = 31/5, a_{i6}^* = 17/5, a_{i7}^* = 59/420$$

Therefore, the initial matrix is established as below:

$$
A^* = \begin{bmatrix}
1 & 12/5 & 7/15 & 132/25 & 2244/125 & 31/15 & 1829/2100 \\
5/12 & 1 & 7/36 & 11/5 & 187/25 & 31/12 & 1829/5040 \\
15/7 & 36/7 & 1 & 396/35 & 6732 & 93/7 & 5847/2940 \\
25/132 & 5/11 & 35/396 & 1 & 17/5 & 155/132 & 1829/11088 \\
125/2244 & 25/187 & 175/6732 & 5/17 & 1 & 775/2244 & 9145/188496 \\
5/31 & 12/31 & 7/39 & 132/15 & 2244/775 & 1 & 59/420 \\
2100/1829 & 5040/1829 & 2940/5487 & 11088/1829 & 188496/9145 & 420/59 & 1
\end{bmatrix}
$$
Based on the reflexive principle, and principle that rows and columns are proportional to the others, the missing elements are filled in, hence a consistent judgment matrix $A^*$ is constructed.

According to the calculation, it comes to $W = (0.200, 0.081, 0.419, 0.037, 0.011, 0.032, 0.220)^T$. Similarly, for Figure3, by using the same calculation processes, it comes to $W = (0.191, 0.080, 0.408, 0.036, 0.034, 0.031, 0.220)^T$.

### 4.2. Optimization results

On the basis of foundational theory on Hadamard Convex Combination, expert matrix $A_1, A_2, A_3, A_4, A_5$ above is selected according to consistent ratio, to take correspondent matrix aggregation. For the purposes of facilitating study, this paper set various expert judgment matrixes on equal weights, that is, let $\lambda_e = (0.2, 0.2, 0.2, 0.2, 0.2)$.

According to the calculation from $\bar{A}$, it comes to $W = (0.200, 0.119, 0.362, 0.068, 0.035, 0.025, 0.191)^T$.

By using the square law, it comes to $CR = 0.036 < 0.1$.

Similarly, According to the calculation from $\bar{A}$.

$W = (0.192, 0.112, 0.352, 0.067, 0.034, 0.026, 0.217)^T$.

By using the square law, it comes to $CR = 0.032 < 0.1$. Analyze the importance list of the index system $G = (G_1, G_2, G_3, G_4, G_5, G_6, G_7)$ listed above.

1. $G_3 > G_7 > G_1 > G_2 > G_4 > G_6 > G_5$; 2. $G_3 > G_7 > G_1 > G_2 > G_4 > G_5 > G_6$.

Based on the above sorting results, the errors are the second and third places of the column names in $G_1$ and $G_7$, and the sixth and seventh places of $G_5$ and $G$.

In combination with the results of the above scheme, there are $G_7 > G_1$ in the sort result 124 and $G_1 > G_7$ in the 3 which can support the sorting result from the other schemes in which the convex combination is significantly different. The result is unreasonable and should be deleted [5]. In 124, $G_5 > G_6$ of 24 and $G_6 > G_5$ of 1 are excluded. Therefore, this paper believes that a reasonable sorting scheme is:

$\tilde{W} = (0.190, 0.089, 0.378, 0.055, 0.039, 0.029, 0.220)^T$

For the aggregated expert matrices $A_1, A_2, A_3, A_4, A_5$.

$\tilde{W} = (0.190, 0.089, 0.378, 0.055, 0.039, 0.029, 0.220)^T$ should be selected as the weight of the indicator system $G = (G_1, G_2, G_3, G_4, G_5, G_6, G_7)$.

### 5. Conclusion

The case calculation, through the multi-stakeholder cooperation group decision risk evaluation, achieves the consensus of multi-stakeholder decision-making information. This paper adopts BP neural network algorithm to simplify the calculation process of group decision making. The concept is clear, the meaning is clear, the calculation is not very complicated and easy to implement by computer.
It can be easily applied to computer decision support system, which can be popularized and applied in group decision calculation.

Acknowledgments

This work was financially supported by Shaanxi province science and technology plan project: Shaanxi province innovation ability support plan project - soft science research plan. Project Number: 2019KRM093.

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