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Retraction

Retracted: Analysis of Risk Assessment of Overseas Infrastructure Projects Integrating BP-ANN Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] C. Li and J. Zhou, "Analysis of Risk Assessment of Overseas Infrastructure Projects Integrating BP-ANN Algorithm," *Security and Communication Networks*, vol. 2022, Article ID 7864665, 13 pages, 2022.

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Research Article

Analysis of Risk Assessment of Overseas Infrastructure Projects Integrating BP-ANN Algorithm

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In order to improve the risk assessment effect of infrastructure projects, this paper combines the BP-ANN algorithm to conduct risk assessment and analysis of overseas infrastructure projects to avoid the problem of slow learning and speed up network learning. Moreover, this paper normalizes the input value, and redefines the concept of risk on the basis of previous research. In addition, this paper sets up to record the basic information and risk-related information of the project. In order to verify the effectiveness of the algorithm, this paper predicts the training data, test data, and verification data, respectively, to verify the effectiveness of the algorithm, and collects existing overseas infrastructure project cases as samples to perform the simulation experiments. The experimental study shows that the risk assessment model of overseas infrastructure projects that integrates the BP-ANN algorithm proposed in this paper has a good risk analysis effect.

1. Introduction

At present, in the context of the slow recovery of the global economy, the pure pursuit of export growth in international trade can easily cause many frictions and contradictions. The "going out" foreign investment method is relatively easy to accept, and the "soft landing" investment method to deal with external demand is obviously a better path than simply exporting. Moreover, by implementing the "going out" investment method, large infrastructure companies can effectively drive the output of China's higher value-added products, such as the investment and construction of transportation infrastructure and subsequent management and operation. In addition, it is also in line with the direction of the country's supply-side reforms and the ultimate goal of industrial upgrading.

The environment faced by overseas infrastructure projects is very complex and uncontrollable. For example, the payback period of investment in overseas infrastructure projects is long, and long-term investment contract relationships must be planned, and long-term investment contracts are quite difficult to implement. Secondly, the planning of public facilities has a profound impact on the public, as well as a great impact on national security, economic development, and the environment. In addition, the object of the transaction is the government, because the government can use public opinion as a reason for changing policies, and use its power to change relevant legal provisions and influence court decisions. Therefore, it is not easy for private organizations to find a dynamic balance between environment, capability, and strategy when formulating strategies and goals [1].

Risk identification and assessment rely too much on experience, and mainly rely on the experience of experts, which is more subjective. Another method is to analyze the data accumulated over the years. However, the various countries outside the country are very different, and the accumulation of relevant data is seldom and has not reached a sufficient scale to support the judgment and management of project risks [2]. The risk sharing mechanism is not reasonable enough. Over the years, many domestic and foreign experts have conducted research on overseas infrastructure models, but they still lack a large number of specific case experience support in terms of actual operation. The overseas infrastructure model structure is complex, and risk management is, to a large extent, the key to the success of overseas infrastructure projects. However, in practice, the private sector often enters the market after the project plan is determined, and the public sector has allocated the main risks of overseas infrastructure projects, resulting in an unreasonable share of the public-private partnership [3].

The risk management system is not sound. The risks of overseas infrastructure projects come from various risks such as international politics, economy, law, and projects. The demands of different stakeholders are very different. The construction of their risk management system is very important because the risks of each project are different. All the same, there is also a lack of a widely applicable risk management system. The management capabilities of private institutions need to be improved. The comprehensive capabilities and social responsibilities of private organizations need to be improved. For example, there is insufficient research on investment business policies in different overseas countries, and the effectiveness of related management such as its own investment strategy formulation, system construction, investment risk monitoring, and evaluation is not high. The government's role is insufficient. Under the overseas infrastructure model, the responsibility of government departments is to adopt good policy advantages to create a good investment and construction environment for the operation of overseas infrastructure projects, and to obtain certain benefits to ensure the quality of public facilities or services. However, the governments of some foreign countries are not perfect in policy formulation and supervision, and they have not played the role of the government well.

The topic selection of this paper is innovative. Through literature research, it is found that most of the PPP project research focuses on the transportation and municipal project industries, and rarely involves the cultural industry. In this paper, through the combination of qualitative and quantitative analysis, the BP-ANN algorithm is used to identify the risk factors of overseas projects, and then the analytic hierarchy process is used to evaluate the risk factors. The combination of subjective experience and objective data not only makes up for the purely subjective one-sidedness but also overcomes the limitations of pure objectivity. Through case analysis, risk control measures are proposed to provide reference for effective risk management of other projects.

In order to explore the risk assessment effect of overseas infrastructure projects, this paper constructs the BP-ANN algorithm, and uses the fusion algorithm to carry out the project risk assessment system to improve the risk assessment effect of overseas infrastructure projects.

2. Related Work

Literature [4] proposed that the definition of fuzzy set does not connect a given set with fuzzy elements. Due to the unclear and difficult to quantify factors in reality evaluation, fuzzy set theory uses mathematical methods to formulate and apply it for a suitable framework. Literature [5] describes a fuzzy connection expert system with learning ability, which adopts a fuzzy operator method for knowledge acquisition and allows the rule to be transformed into an equivalent connection network. The system developed by the fuzzy operator method was used to judge the credit risk of corporate loans and compared it with the existing conventional system. Literature [6] believes that because the definition of class is inherently vague, fuzzy set theory can provide a suitable framework for pattern classification. Based on the fuzzy pattern matching process, the fuzzy set theory is discussed, which combines partial matching values of given attributes. A new method based on fuzzy integral and possibility theory is proposed, and the statistical method and the supervised learning process are critically tested with the experimental test results of actual data.

Literature [7] proposes that the Analytic Hierarchy Process (AHP) allows rank maintenance (ideal mode) or allows rank reversal (distribution mode), which is an additive synthesis of priorities, and is therefore used in general feedback network decision-making structures with a hierarchical structure. Multi-linear vectors to reduce multi-dimensional measurements to a one-dimensional ratio scale. When using the analytic hierarchy process, the conditions under which the feature vector is sensitive to the judgment change should be determined. In order to extend the scale from 1–9 to 1-R, the selected indicators should be homogeneous. The analytic hierarchy process is simple, practical, flexible, and convenient. It combines qualitative indicators with quantitative indicators, decomposes the evaluation objectives in layers, compares the indicators at each level, and converts the comparison results into a judgment matrix, and checks the consistency of the constructed judgment matrix, to achieve the evaluation goal [8].

Literature [9] believes that the core of risk management is to accurately find out all possible risk factors of the project. Literature [10] proposes that the risks of overseas infrastructure projects can be divided into international risks and project risks. The former is caused by differences in political economy and investment environment, while the latter is related to the project level, such as construction, operation, financing, income. Literature [11] divides the risks from the different development stages of the project life cycle. Literature [12] believes that the risks of overseas infrastructure models can be classified from two perspectives, namely, whole-process risks and partial risks. The literature [13] analyzes the internal and external environment of the overseas infrastructure model, which is classified into macro risks, medium risks, and micro risks. The external risks of the project are macro risks, the internal risks in project implementation are medium risks and the project benefits. The way of cooperation between stakeholders and the risk of income distribution are micro-risks. Literature [14] divides overseas infrastructure risks into specific risks and system risks. Specific risks refer to risks related to the project, and system risks mainly refer to risks related to the global political and economic environment. Literature [15] classified the risks of overseas infrastructure projects from two perspectives: macro risks and micro risks. The macro aspects mainly include political, economic, legal, and natural reasons, and the micro aspects mainly include financing, construction, operation, and cooperation. Researched from the perspective of micro-risk factor list identification, the literature [16] analyzed the risks of overseas infrastructure projects from the international level, project level, and customer level, citing the main sources of risks, including economic, political, legal, and technical, financing, construction, operation, user purchase, and other risks. Literature [17] divides the risks of overseas infrastructure into 7 categories in more detail: political, legal, credit, construction, market, financial, and natural environment risks, and identifies 33 key risk indicators. Literature [18] uses a questionnaire survey method to identify 20 key risk factors for overseas infrastructure projects. Literature [19] analyzes the overseas investment business of Chinese companies and proposes that the main sources of risk include: politics, corporate culture, information management, vicious competition, single investment structure, and insufficient international management capabilities. Literature [20] put forward five sources of risk: market, resources, capacity, and legal risks. Literature [21] analyzed the main risks in overseas infrastructure projects and put forward a list of risks.

3. Risk Assessment Combined with BP-ANN Algorithm

The establishment of neural network is based on MATLAB, which can easily call the neural network toolbox to establish the network model.

In order to avoid slow learning speed and speed up the network learning speed, the input value can be normalized so that the input signal of all samples varies between −1 and 1.

In MATLAB, the normalization of the data is generally processed by the mapminmax function, and the formula for the function is [22]:

$$(p_i)_n = 2 \times \frac{p_i \cdot (p)_{\min}}{(p)_{\max} \cdot (p)_{\min}} - 1. \tag{1}$$

Among them, (p_i) and p_i are the standard value and the original value of the parameter in the experimental data group, respectively, and $(p)_{\max}$ and $(p)_{\min}$ are the maximum and minimum values of the original value of the corresponding parameter, respectively.

When the final data is output, the result is denormalized to obtain the standard value of the result. The denormalization function can be expressed by (2):

$$p_i = \frac{\left[(p_i)_n + 1\right]\left[(p)_{\max} - (p)_{\min}\right]}{2} + (p)_{\min}. \tag{2}$$

The range of the parameters after data normalization is between −1 and 1, avoiding the generalization problem of the network. At the same time, the convergence speed of NNs is accelerated.

In this paper, a feed-forward NNs model is established. A combination of tan-sigmoid and linear transform functions is used in multi-layer NNs and applied to the hidden layer and output layer, respectively.

The algorithm designs the number of network layers and the number of neurons contained in each layer. The number of input and output neurons of NNs is determined by the actual problem to be solved, which has nothing to do with network performance. This article considers 10 influencing parameters, that is, set 10 input values, and set an output value, that is, the shear capacity.

The superiority of the network greatly depends on the number of hidden layers and the number of neurons in the hidden layer. In order to select the optimal network, we generally refer to the results obtained by empirical formulas (3) and (4) to perform comprehensive test verification.

$$l = \sqrt{(m+n)} + a, \tag{3}$$

or

$$l = \sqrt{\left(0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35 + 0.51\right)}. \tag{4}$$

Among them, m and n are the number of neurons in the input layer and the number of neurons in the output layer, and a is a constant between 1 and 10.

The algorithm sets the learning rate (Ir) and momentum factor (mc). Based on experience and actual conditions, Ir-0.01 and mc = 0.4 are selected. At the same time, a convergence condition needs to be set, and the selection of this condition can neither be too harsh nor too relaxed. Too harsh conditions will lead to too fast convergence and inaccurate results. Too loose conditions will result in too slow calculation speed considering comprehensively.

When any one of the conditions is met, the algorithm stops training and outputs the result. The matrix expression of the BP-ANN structure is [23]:

$$O = f_3\left(LW_2 f_2\left(LW_1 f_1\left(IW \times I + b_1\right) + b_2\right) + b_3\right). \tag{5}$$

In (5), f_1, f_2 represents the hidden layer of the nonlinear (tan-sigmoid) function (6), and f_3 represents the application of the linear transform function (7) to the output layer. Its function expression form is

$$y_{ij} = \frac{1}{1 + \exp\left[-IW_{ijk}X_k + \theta_{ij}\right]}. \tag{6}$$

In the formula, y_{ij} is the output of the j-th neuron in the i-th layer, X_k is the k-th input, θ_{ij} is the j-th threshold of the i-th layer, and θ_{ij} is the weight of the i-th layer X_k corresponding to y_{ij} [24].

$$O = \sum_{k=1}^{n} LW_{3k} \times y_{3k}. \tag{7}$$

The BP-ANN model predicts the training data, test data, and verification data, respectively, and the results are shown in Figure 1. According to the comparison between the predicted results of the three sets of test data and the test values, the following results can be obtained. (1) The mean and variance of Vses/V xatit of training group, test group, and verification group are 1.049, 1.031, 0.977, and 0.012,

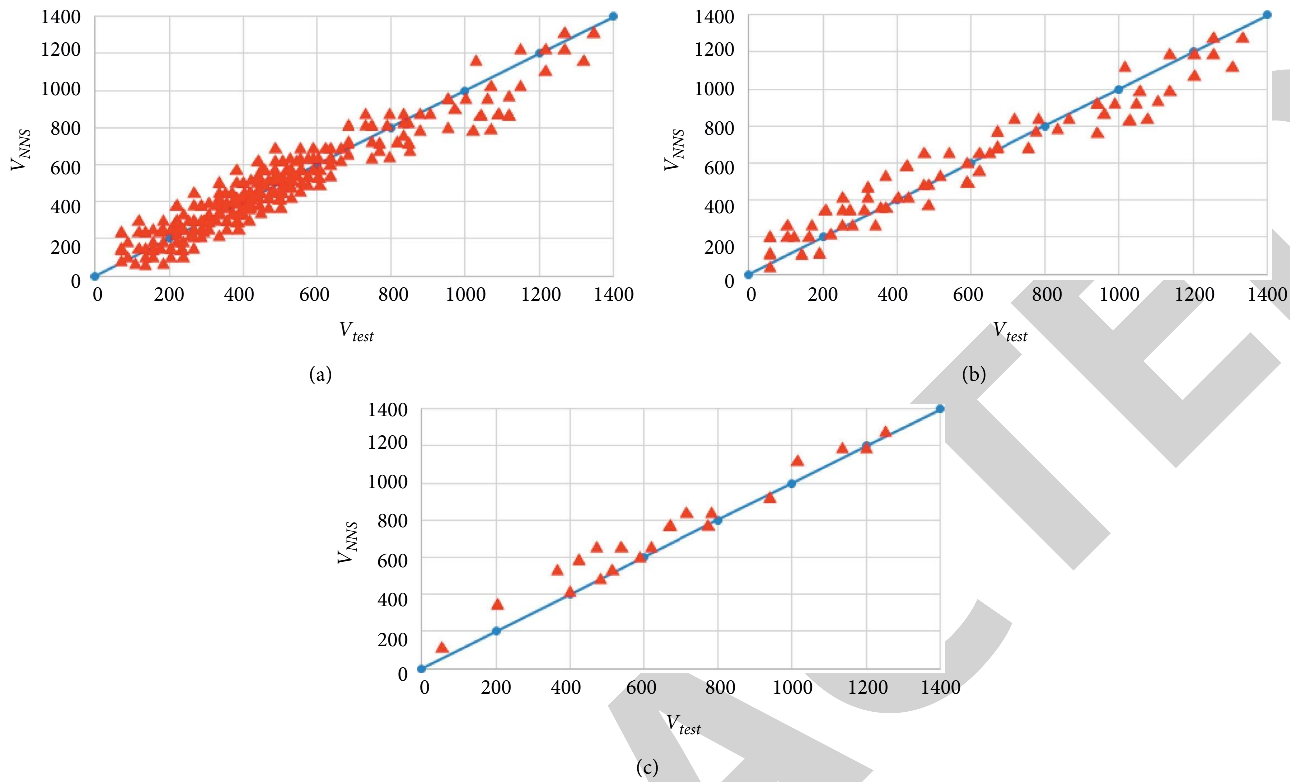

Figure 1: Comparative analysis of model training. (a) Training group. (b) Test group. (c) Verification group.

0.059, 0.020, respectively. (2) The shear capacity predicted based on the BP-ANN model is basically consistent with the experimental value, and the dispersion is small.

Monte Carlo (MC) method is a mathematical simulation method. This method uses random probability distribution sampling to construct random input variables in a given model, and then determines its sensitivity factors based on the model calculation values of random input variables. The analysis process is shown in Figure 2.

The sensitivity analysis (SA) method is a very practical tool in the process of modifying the parameters of the model. Through SA method analysis, we can intuitively see the influence of each input parameter in the model on the output value. Therefore, the input parameters with greater sensitivity can be given priority in the model optimization process. The parameters that are less sensitive, that is, have minimal impact on the output value of the model, can be eliminated, and the model can be optimized by reducing the complexity of the model.

At present, the importance of the SA method is recognized by most scholars, but most researchers have not made effective use of the SA method in the process of establishing the model. The main reason is that the calculation process is more complicated and the calculation results are difficult to explain clearly.

Sensitivity analysis includes global sensitivity analysis (Global Sensitivity Analysis, GSA) and local sensitivity analysis (Local Sensitivity Analysis, LSA). LSA only calculates the influence of a single parameter on the output value of the model, and the average value of other parameters. However, GSA calculates the total influence of multiple parameters on the model output value, and analyzes the influence of the coupling between the parameters on the model output value. The difference between LSA and GSA is that each input value changes within an infinite or finite range, and the change in model output value caused by a certain input value change is global. That is, the change of model output value is carried out under the joint action of all input values. GSA method can be divided into quantitative GSA method and qualitative GSA method. The qualitative GSA method only qualitatively analyzes the influence of the change of each input value of the model on the model result, also known as the factor screening of sensitivity analysis, which can sort the sensitivity of each input value of the model with a small amount of calculation. The quantitative GSA law is to quantitatively give the contribution rate of each input value change to the model output value change [25].

The advantage of LSA is strong operability. However, LSA also has several shortcomings. It only considers single factor changes, and can only analyze a single factor individually each time, which is very complicated in terms of calculation.

The LSA method only analyzes single-factor variables each time, so its calculation results ignore the influence of the coupling between the input parameters of the model on the output value. This is because when a single factor variable is analyzed, the changes of other input parameters will also affect the final sensitivity value. Therefore, the current research on SA is gradually biased towards the GSA method.

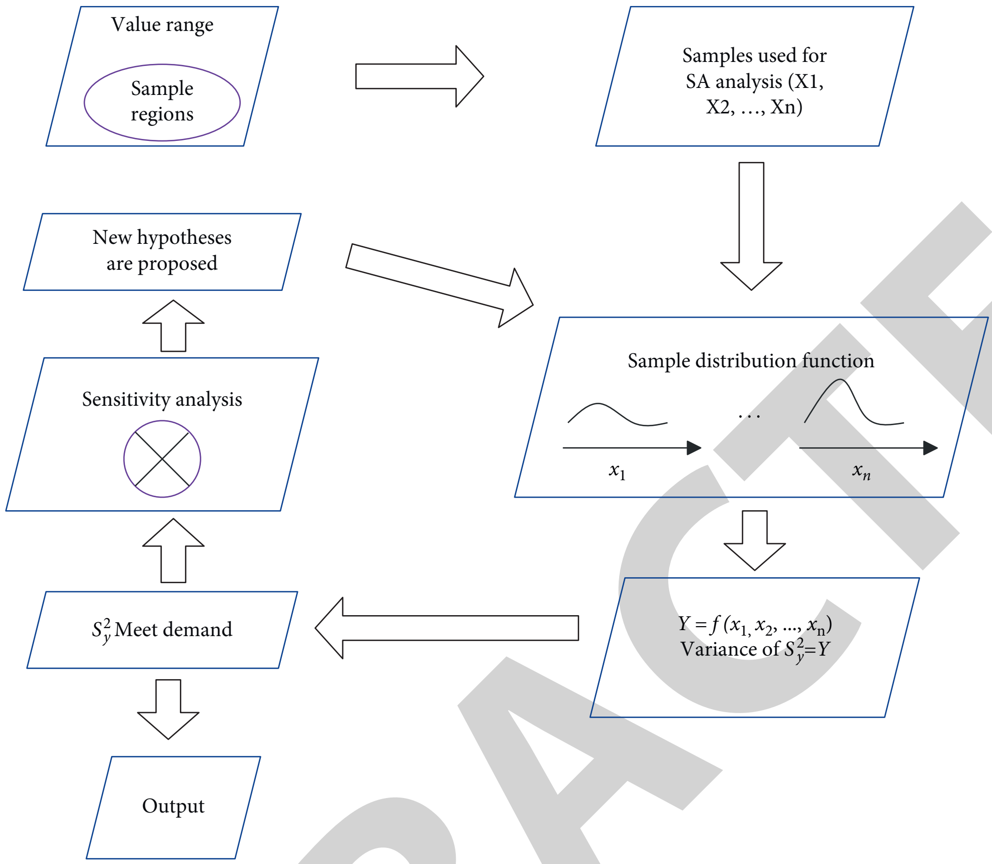

Figure 2: Sensitivity analysis steps.

As the domestic recognition of GSA is not high, almost all adopt LSA method at present.

LSA is also called single conversion method. Its calculation method is to control an input parameter separately, and set a fixed value for other parameters, and calculate the sensitivity value through the change of the model output value when the input parameter changes. There are two main methods. One is the single-factor transformation method, that is, the selected input parameter is incremented or decremented by 10% each time. The other is partial differentiation. Generally, the sensitivity coefficient is used as the calculation standard for the results of the SA method. The common sensitivity coefficient expressions are [26]:

$$S_i = \frac{\mathrm{d}v}{\mathrm{d}p_i}. \tag{8}$$

In the formula, p_i is the sensitivity value of the i-th input parameter, v is the predicted value of the model, and p_i is the i-th parameter.

The general view is that if the model is less sensitive to parameter errors, then the model is suitable for different situations, but this view is wrong. Because the parameter error in actual application may be far more than the change within the range of 10% or 20%, and may even reach a change of 2 times or 10 times. If the initialization parameters of the model are wrong, the model is insensitive to the 10% amplitude of parameter changes.

The global sensitivity analysis is as follows:

3.1. Multiple Regression Method. The multiple regression method based on Latin Hypercube Sampling (LHS) was published in 1979 by McKay. This method divides the cumulative distribution of the input parameter probability into multiple equidistant intervals, and LHS is more comprehensive and efficient than the ordinary random allocation sampling method. It divides the y-axis of each input value distribution probability function into multiple equidistant intervals from 0 to 1, and each equidistant interval corresponds to an equal probability parameter interval on the x-axis. Therefore, the value range of the probability function is divided into multiple equal probability parameter intervals. On the y-axis, the algorithm randomly samples in each divided interval to obtain the corresponding parameters on the x-axis.

For example, there are n input parameters in the model, and the probability distribution of each input parameter is equally divided into m intervals, and there are $n \times m$ sample combinations. In fact, the LHS method only takes m samples. The method is to list the values of the n input parameters as a matrix with n rows and m columns, and to disorder the value of each column of the matrix to obtain m inputs of each parameter. Each row of the matrix is used as the input value of each parameter, and the predicted value is

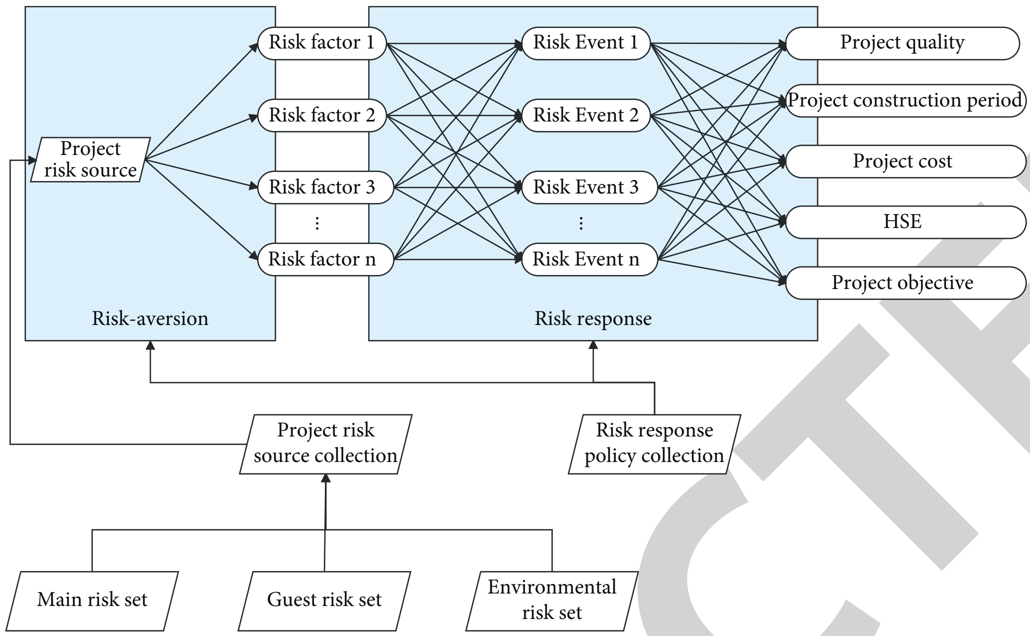

Figure 3: The risk assessment model for overseas infrastructure projects that integrates BP-ANN algorithm.

obtained by inputting the model. The sensitivity can be expressed by the multiple regression coefficient between the predicted value and the input value.

3.2. Extended Fourier Amplitude Sensitivity Test Method. The extended Fourier amplitude sensitivity test (EFAST) obtains the expansion of the Fourier series by Fourier transformation. According to a suitable search function, the model $y = f(x_1, x_2, \ldots, x_n)$ can be transformed into $y = f(k)$ through Fourier transformation:

$$\begin{aligned} y &= f(k) \\ &= \sum_{-\infty}^{+\infty} \left\{ A_j \cos\ jk + B_j \sin\ jk \right\}. \end{aligned} \tag{9}$$

Among them,

$$\begin{aligned} A_k &= \frac{1}{2\pi} \int_{-\pi}^{+\pi} f(k) \cos\ jk\mathrm{d}k, \\ B_k &= \frac{1}{2\pi} \int_{-\pi}^{+\pi} f(k) \sin\ jk\mathrm{d}k. \end{aligned} \tag{10}$$

In the formula, $j \in Z = \{-\infty, \ldots, -1, 0, 1, \ldots, +\infty\}$.

The expansion curve of the Fourier series is defined by $\Lambda_j = A_j^2 + B_j^2$, where $j \in Z$, $A_{-j} = A_j$, $\Lambda_{-j} = \Lambda_j$. The variance of the model result caused by the uncertainty of parameter x_i is

$$\begin{aligned} V_i &= \sum_{p \in Z^0} \Lambda p w_i \\ &= 2 \sum_{p=1}^{+\infty} \Lambda p w_i. \end{aligned} \tag{11}$$

Among them, $Z^0 = Z - \{0\}$. The total variance is

$$\begin{aligned} V &= \sum_{j \in Z^0} \Lambda_j \\ &= 2 \sum_{j=1}^{+\infty} \Lambda_j. \end{aligned} \tag{12}$$

Among them, $[-\pi, \pi]$ is taken at equal distances in the interval of b, and each k corresponds to an input parameter model after multiple runs of the model, and A_j and B_j can be approximated by the following equations:

$$\begin{aligned} A_j &= \frac{1}{Ns} \sum_{k=1}^{Ns} f(s_k) \cos(j s_k), \\ B_j &= \frac{1}{Ns} \sum_{k=1}^{Ns} f(s_k) \cos(j s_k). \end{aligned} \tag{13}$$

Among them, $j \in \overline{Z}$, and N_s is equal to the number of samples, $\overline{Z} = \{-Ns - 1/2, \ldots, -1, 0, 1, \ldots, Ns - 1/2\}$. From the frequency w_i corresponding to A_j and B_j and the parameter x_i, the variance Vi corresponding to each parameter and the total variance V of the calculated value are obtained by formulas (11) and (12). Through $S_{i_1, i_2, \ldots, i_s} = V_{i_1, i_2, \ldots, i_s} / V$, the sensitivity of each parameter can be obtained. Through $S_{T_i} = \sum S_{(i)}$, the overall sensitivity of parameter x_i can be calculated.

The advantage of EFAST is that the amount of calculation is much smaller. EFAST only needs one sampling to obtain the primary sensitivity and total sensitivity of a certain parameter at the same time. However, EFAST requires that the input parameters of the model are irrelevant.

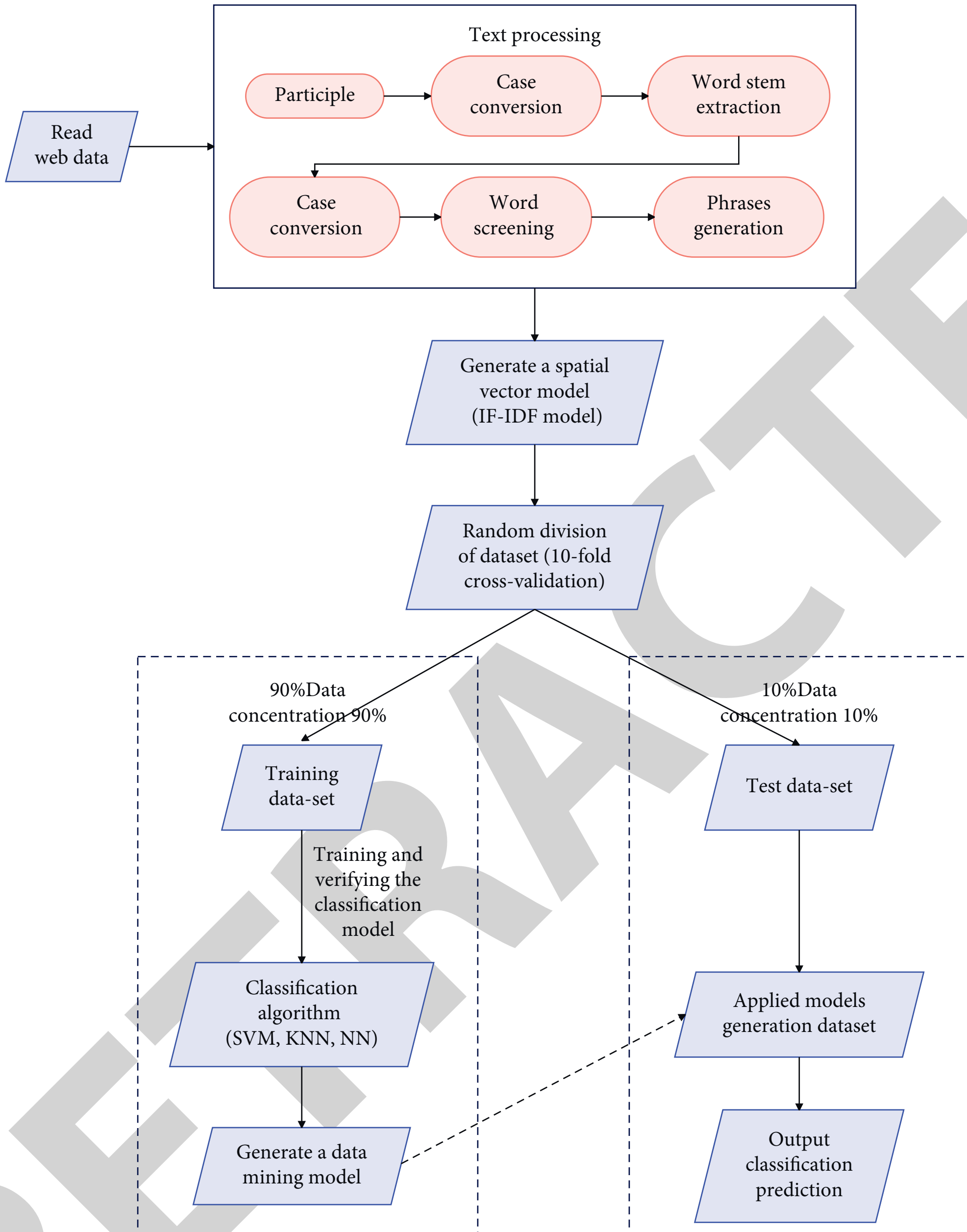

Figure 4: Schematic diagram of the text classification model process.

3.3. Morris Method. The Morris method maps the value range of each parameter to [0, 1], and then discretizes to consider the $m \times k$ $(m = k + 1)$ matrix B:

$$\begin{bmatrix} 0 & 0 & 0 & \dots & 0 \\ 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}, \tag{14}$$

and increment $\Delta B_{i,j} = s/n - 1$, where s is the variable factor and n is the number of parameter samples. Only one parameter of two adjacent rows in the matrix $\triangle$B has a different value, and the increment is $\triangle$. Therefore, by using two adjacent rows as model input parameters, the output values y_1 and y_2 of the model can be obtained.

$$\partial_i(x) = \frac{(y_1 - y_2)}{\Delta}. \tag{15}$$

Formula (12) can calculate the sensitivity of model input parameters. The sensitivity of all n input parameters can be obtained by taking all n groups of adjacent row elements as the input parameters of the model. Therefore, it can be obtained that the sensitivity of n input parameters can be obtained by random sampling once, so the calculation efficiency is very high.

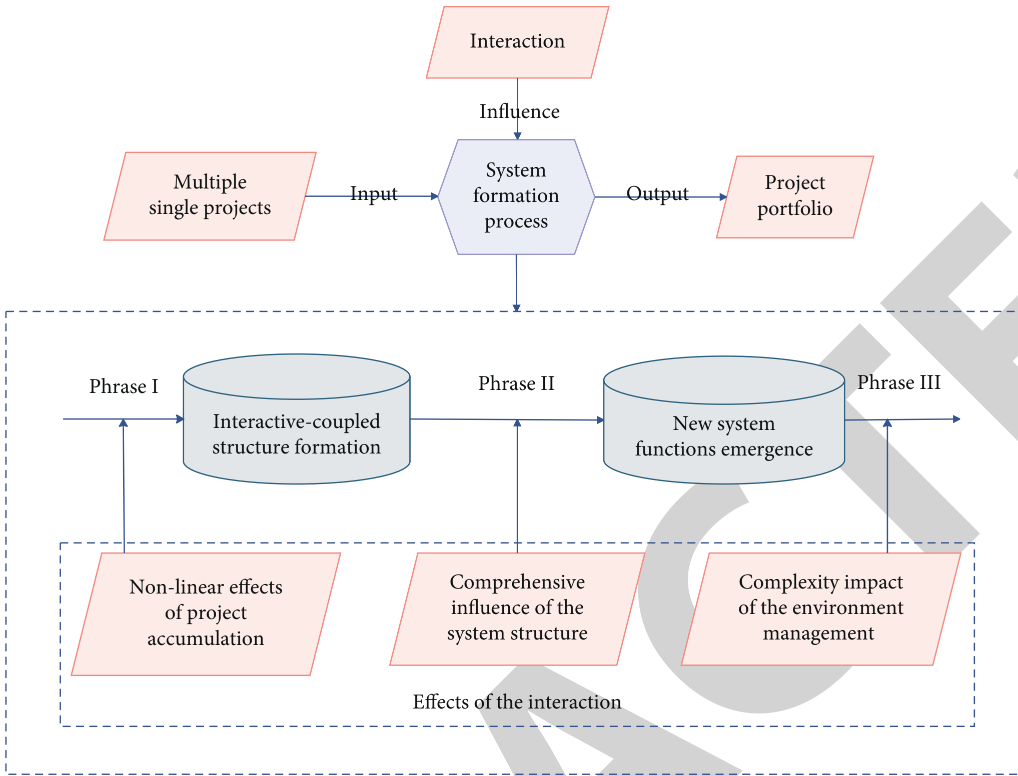

FIGURE 5: The formation process of the project portfolio system.

The Morris method can be used to calculate the average value and standard deviation. The average value represents the sensitivity of the input parameter, and the order of sensitivity is determined by sorting from large to small. The standard deviation can represent the degree of coupling between input parameters. A small standard deviation means that the degree of coupling between the input parameter and other input parameters is small. Conversely, if the standard deviation is large, it means that the degree of coupling between the input parameter and other input parameters is large.

4. Risk Assessment of Overseas Infrastructure Projects Integrating BP-ANN Algorithm

The objective function model of this paper is as follows.

4.1. Establish a Risk Hierarchy Index Structure.

(1) Target layer

(2) Criterion layer

(3) Subcriteria layer

4.2. Construct the Judgment Matrix. Construct the judgment matrix according to the risk hierarchy and assign values.

$$A = \begin{bmatrix} A_{11} & \ldots & A_{1n} \\ \ldots & \ldots & \ldots \\ A_{n1} & \ldots & A_{nn} \end{bmatrix}. \tag{16}$$

A is represented as a judgment matrix.

4.3. Calculate the Eigenvectors of the Matrix and Calculate the Index Weights. (1) Sum the columns of the matrix

(2) Normalize each column

$$B_{ij} = \frac{A_{ij}}{\sum A_{ij}}. \tag{17}$$

The value of $\sum A_{ij}$ is the sum of the values in the columns. Use the above formula to obtain a new matrix B.

(3) Sum each row and calculate the feature vector.

(4) Normalize the feature vector to get the index weight

4.4. Consistency Test. (1) Calculate the largest eigenroot.

$$\lambda_{\max} = \frac{\sum (\mathrm{AW})i}{\sum nWi}. \tag{18}$$

A is multiplied by w, which means that the two matrices are multiplied, and the result is a column vector, and then each element in the column vector is divided by the product of the order and the corresponding weight.

(2) Judge the consistency index of the matrix.

$$\mathrm{CI} = \frac{\lambda_{\max-n}}{n-1}. \tag{19}$$

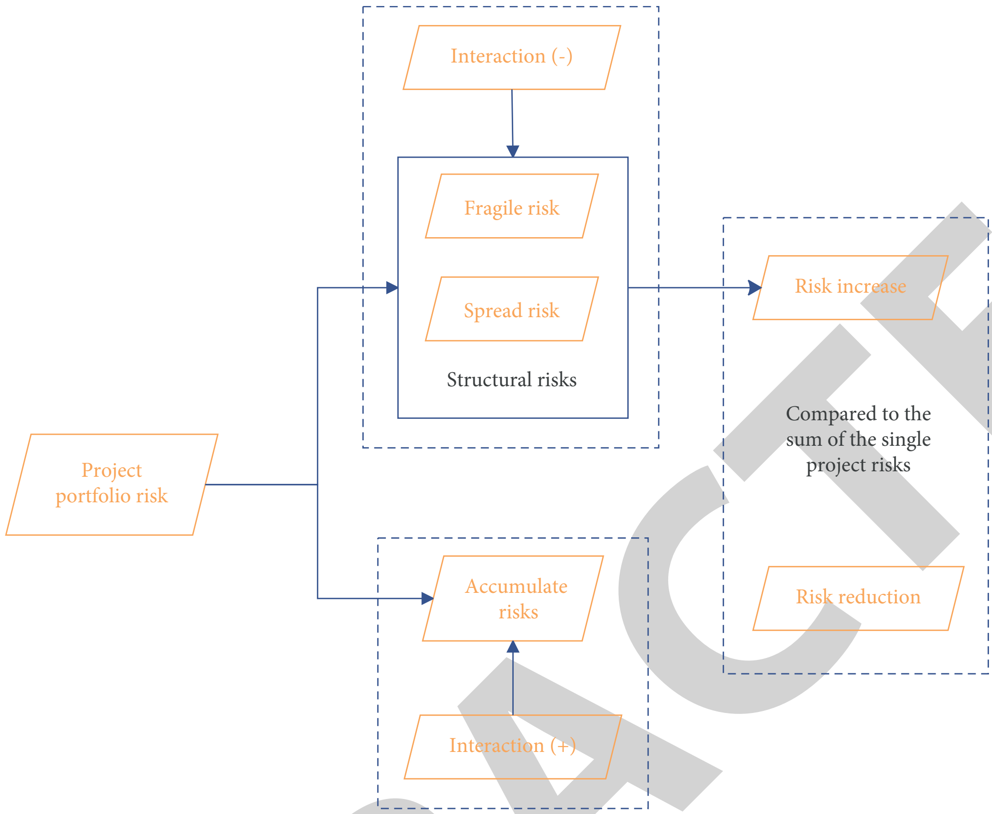

Figure 6: The risk composition of the project portfolio from the perspective of interaction effects.

(3) Obtain the consistency ratio.

$$CR = \frac{CI}{RI}. \tag{20}$$

RI is the standard value of matrix order, when $CR < 0.1$, the inconsistency of A is acceptable.

In this study, in order to construct information about the whole process of recording engineering project risk from generation to result, the related concepts of risk are redefined on the basis of previous research, To set the model hyper-parameters of ANN, using the cross-validation method, setting the target function, and taking the strategy for avoiding overfitting, and an information table is set up to record basic project information and risk-related information. The risk assessment model of overseas infrastructure projects that incorporates the BP-ANN algorithm can be represented in Figure 3.

In this study, a variety of classification algorithms are used to compare with each other to construct the classification model. Although the types of algorithms used are different, the classification models are all based on the same process shown in Figure 4. The implementation process of the text classification algorithm in Rapidminer is similar to the construction process of the above decision tree.

A single project is the constituent element of the project portfolio, and the accumulation of elements is the first step in the formation of the project portfolio system. The process of project accumulation is not carried out independently, and it will be affected by the nonlinear effects of different scales of interaction effects. The accumulated project group has an interactively coupled system structure, and the comprehensive effects of various associations on the system structure give the project portfolio new functions and behavior characteristics. This is the second step in the formation of the system. The function and behavior of the project portfolio are affected by the management process and the activities of the managers. Various management decisions, regulations, and implementation plans will affect the operation of the project portfolio system, which constitutes the third step of the formation of the system. The process of project portfolio system formation is shown in Figure 5.

The negative effect of the interaction effect on the project portfolio risk refers to the fact that under the influence of the interaction effect, the project portfolio has new risks that a single project does not have, which makes the overall risk of the project portfolio increase. Project portfolio is a complex system that is different from a single project. It has system functions and behavioral characteristics that a single project does not have. When new functions emerge, it also brings new risks. Based on the evolution process of project portfolio risk, the comprehensive impact of interaction effects on the system structure and the complexity of the management environment are the sources of its negative effects. Based on the different utility of interaction effects on project portfolio risk, the composition of project portfolio risk is shown in Figure 6.

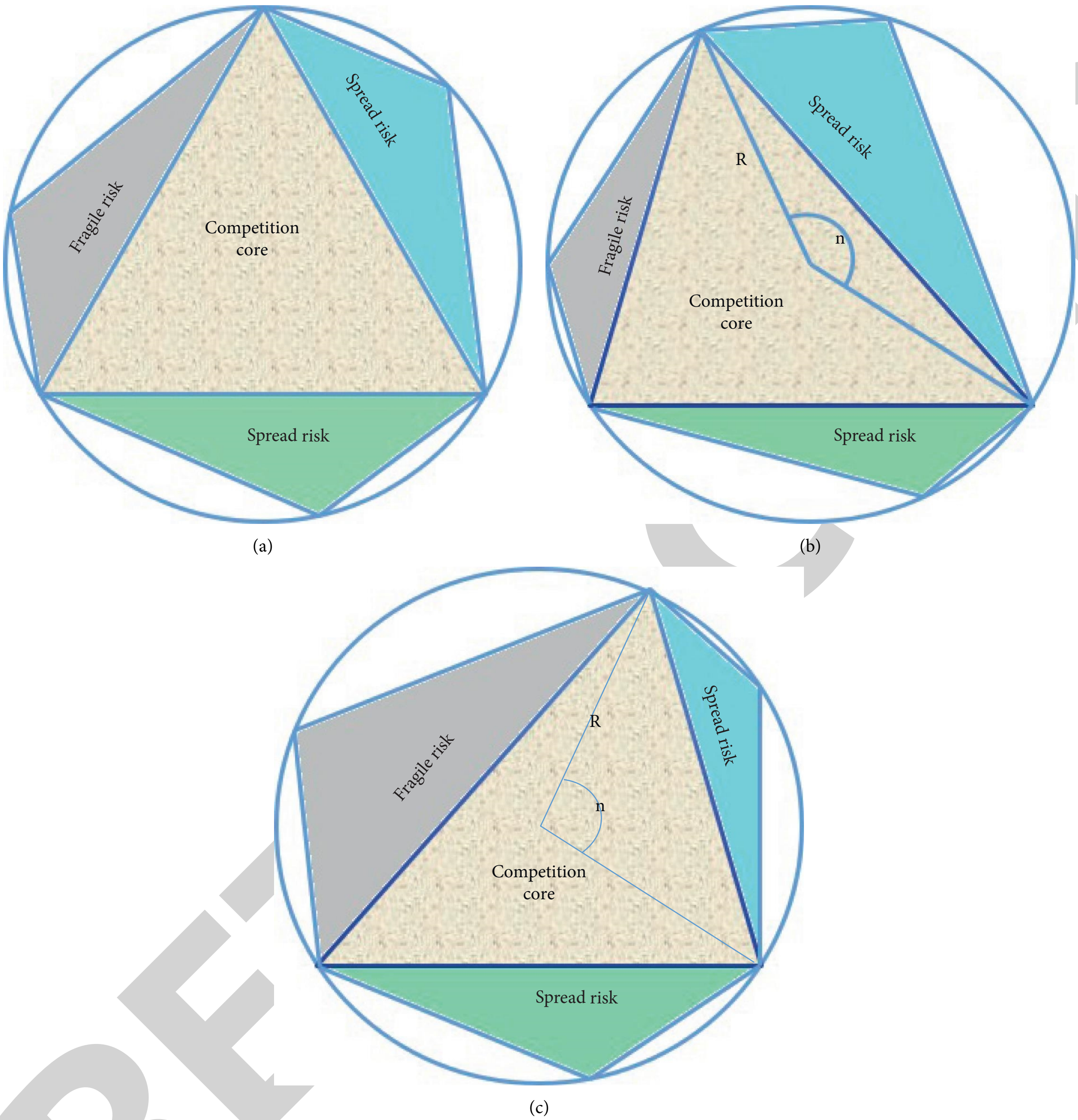

Figure 7: Competitiveness measurement architecture. (a) Competitive strength structure of project portfolio risk. (b) Progressive. (c) Conserve.

Construct a comprehensive measurement framework for project portfolio risk as shown in Figure 7, which is called the competence measurement framework. Competitiveness refers to the power comparison of the risk formed by the different effects of the interaction effect on the overall risk. The competitiveness measurement framework of project portfolio risk comprehensively reflects the competitive situation of the two forces of risk diversification and the addition of new risks. By comparing the magnitude of the two forces, the overall trend of project portfolio risk can be determined.

In Figure 7(a), the triangle at the core of the competition divides the circumcircle into three modules. There is an inscribed triangle for each module, and the area of this triangle represents the utility strength of the corresponding measurement content on the risk of the project portfolio. The core of competition in Figure 7(c) is an equilateral triangle, which divides the three modules equally. However, managers with different attitudes towards risk make the prerequisites for diversifying risks and emerging risks to be different, which leads to the competition results under different split ratios as shown in Figures 7(b) and 7(c). At

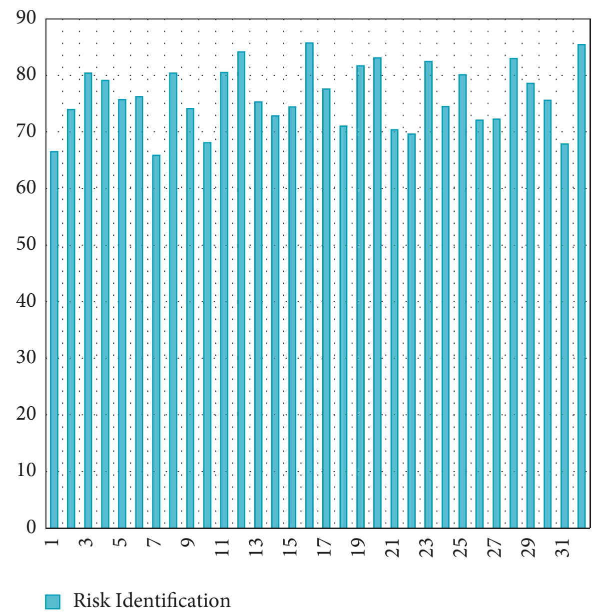

Figure 8: Statistical diagram of risk factor identification data.

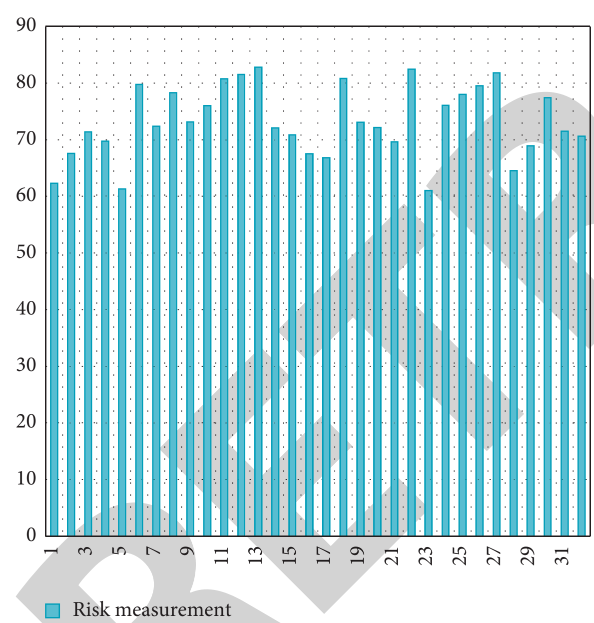

Figure 9: Statistical diagram of risk measurement data.

this time, the core of competitiveness becomes an irregular triangle under the subjective influence of risk.

From the above, the risks of overseas infrastructure projects can be evaluated. Therefore, this paper uses experimental research to verify the effect of the risk assessment model of overseas infrastructure projects that integrates the BP-ANN algorithm. This article collects existing overseas infrastructure project cases through the Internet as a sample, and the risk factors and risk measurement have actual data. On this basis, the system model of this article is used to identify the risk factors and analyze the risk measurement in

Table 1: The risk factor identification effect of the risk assessment model of overseas infrastructure projects that integrates the BP-ANN algorithm.

Sample number	Risk identification	Sample number	Risk identification
1	66.50	17	77.59
2	73.97	18	71.01
3	80.40	19	81.71
4	79.12	20	83.08
5	75.70	21	70.36
6	76.21	22	69.60
7	65.84	23	82.43
8	80.37	24	74.46
9	74.10	25	80.11
10	68.10	26	72.06
11	80.50	27	72.24
12	84.12	28	82.96
13	75.31	29	78.57
14	72.81	30	75.57
15	74.43	31	67.84
16	85.71	32	85.42

Table 2: The analysis effect of risk measurement of the risk assessment model of overseas infrastructure projects that integrates the BP-ANN algorithm.

Sample number	Risk measurement	Sample number	Risk measurement
1	62.28	17	66.84
2	67.59	18	80.83
3	71.37	19	73.06
4	69.72	20	72.12
5	61.33	21	69.62
6	79.76	22	82.45
7	72.38	23	61.02
8	78.28	24	76.06
9	73.12	25	78.03
10	75.99	26	79.52
11	80.75	27	81.80
12	81.50	28	64.52
13	82.78	29	68.90
14	72.06	30	77.43
15	70.84	31	71.48
16	67.50	32	70.59

these cases, and the statistical accuracy rate is used to verify the effectiveness of the algorithm in this article. The statistical risk factor identification and risk measurement effect evaluation are shown in Tables 1 and 2, Figures 8 and 9, respectively.

The method in this paper is compared with the literature [17], mainly to verify the effect of project risk assessment, and the results are shown in Table 3.

From the above research, it can be seen that the risk assessment model of overseas infrastructure projects that integrate the BP-ANN algorithm proposed in this article has a good risk analysis effect and has a certain effect on improving the risk assessment of overseas infrastructure projects.

Table 3: Comparison of project risk assessment effects.

Number	The method of this paper	The method in [17]	Number	The method of this paper	The method in [17]
1	81.13	75.14	17	83.58	76.41
2	84.86	80.08	18	85.31	80.40
3	84.16	77.11	19	87.82	78.75
4	85.42	74.98	20	82.26	72.71
5	84.36	79.41	21	82.99	76.51
6	81.91	75.14	22	82.52	75.12
7	83.19	74.27	23	86.83	82.12
8	83.21	77.05	24	86.00	75.17
9	83.73	75.06	25	88.49	80.32
10	81.46	71.04	26	85.12	74.08
11	83.33	76.70	27	81.84	74.65
12	86.15	75.42	28	88.21	80.90
13	82.36	72.13	29	82.50	75.50
14	85.50	74.59	30	83.09	76.25
15	88.61	79.33	31	88.51	81.68
16	81.36	74.23	32	87.48	78.14

5. Conclusion

Compared with the general projects, overseas infrastructure construction projects have the characteristics of political relevance, non-profitability, public use, government agency, and huge fixed cost precipitation. In addition, financial risks, income risks, operational risks, and systematic risk management arising from the characteristics of large investment scale, high financing leverage, and long construction and investment cycles are the keys to the success of overseas infrastructure projects. In order to explore the effect of risk assessment of overseas infrastructure projects, this paper constructs the BP-ANN algorithm, and builds a project risk assessment system through fusion algorithms to improve the effect of risk assessment of overseas infrastructure projects. The research shows that the risk assessment model of overseas infrastructure projects integrating the BP-ANN algorithm proposed in this article has a good risk analysis effect and has a certain effect on improving the risk assessment of overseas infrastructure projects.

Data Availability

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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