Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 2638273, 12 pages
https://doi.org/10.1155/2022/2638273

Research Article

Comparative Analysis and Evaluation of Bridge Construction Risk with Multiple Intelligent Algorithms

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Received 11 March 2022; Revised 11 May 2022; Accepted 2 June 2022; Published 15 June 2022

Academic Editor: Rahib Abiyev

Bridge collapse in the construction process is one of the most common bridge accidents; we can see the importance of construction to ensure bridge safety. Site construction safety management mainly relies on checklist evaluation, but the evaluation results are often affected by the ability and experience of the evaluator. Using an artificial intelligence algorithm to realize rapid and accurate risk assessment of the bridge construction process is an effective way and development direction to solve the above problems. In view of the uncertain factors in the process of bridge construction, this paper analyzes and classifies the man-made and environmental risk factors that affect the bridge construction stage by using the 4M1E analysis method. Typical artificial intelligence algorithms are used to construct risk assessment models for bridge construction. And the random forest algorithm is used to analyze and verify the construction example of the FIU bridge.

1. Introduction

With the development of modern technology, bridge construction methods of various new structures and new materials are also developing. However, the newly built bridges are gorgeous in appearance and shape but complicated in structure and construction. As the design and construction are improper or of poor quality, it may cause additional costs or even on-site injuries. In the construction process of such bridges, risk factors are also increasing. The risk factors in bridge construction are not only numerous but also associated with each other, which makes the safety of bridge construction face great challenges.

The application and research of risk management in the engineering field are relatively late, which began in the 1970s. European and American countries apply risk assessment in the nuclear industry to identify potential safety hazards in the construction and use of power plants through safety risk assessment so as to take targeted measures to prevent safety accidents. Subsequently, the application in marine, environmental, and water conservancy engineering gradually matured and formed a relatively systematic research and application results. The application and research of risk management in bridge engineering began in the 1980s, and it has been more than 30 years since the study of ship collision. So far, some achievements have been accomplished in the research of bridge risk management, and some new methods of risk identification, analysis, and evaluation of bridge engineering have been put forward, which involve the design, construction, operation, and maintenance of bridges. Especially in Europe, America, Japan, and other developed countries, the research on risk management has made rich theoretical and practical achievements and quantitative risk assessment has been well applied in engineering practice. However, the research studies on bridge risk management mainly focus on some specific risk situations such as earthquake, vehicle collision, and ship collision, and the research studies on safety management during bridge construction, especially during the construction period of large bridges, are relatively lacking.

In order to scientifically control the risk of bridge construction, since Sorrill [1] of Britain first proposed the concept of risk engineering, many experts and scholars around the world have carried out in-depth studies on the safety risk assessment of bridge construction. Liu et al. [2] proposed and applied the concept and analysis principle of a coupled fault tree to describe the safety accidents in construction sites. Chen et al. [3], considering the subjectivity and incompleteness of traditional risk analysis methods, coupled WBS-RBS to conduct a detailed decomposition of operations and risk units and combined it with AHP to build a construction risk evaluation model. Lu et al. [4] established a bridge risk assessment model based on the Kent index method and concluded that the technical level of construction personnel and site safety management was the main risk factor. In addition, in terms of fuzzy evaluation methods, Ling et al. [5] determined the evaluation indexes and corresponding weights of safety accident risk evaluation on construction site based on the statistical analysis of safety accident cases on construction site and constructed the membership function of fuzzy comprehensive evaluation. Nieto-morote and Ruz-Vila [6] combined fuzzy theory with AHP to evaluate the risk of a certain bridge construction stage. Wang et al. [7], respectively, proposed the risk assessment method based on fuzzy decision, and applied these methods to the assessment of risk analysis of a bridge; the review of an actual bridge with traditional risk assessment methods are compared, and the results show that the proposed several new methods in bridge evaluation have a certain flexibility, practicality, and effectiveness. Abdollahzadeh and Rastgoo [8] adopted fault tree and event tree analysis methods based on fuzzy logic to evaluate the risks in bridge construction projects. Liu et al. [9] studied the construction risk of the double-walled coffer dam pier and applied the fuzzy fault tree theory to evaluate its reliability and safety. Wang and Chen [10] proposed a system decision support method for uncertainty safety risk analysis of subway construction projects based on the fuzzy comprehensive Bayesian network, indicating that this method is effective in estimating the risk level of subway construction projects under uncertain conditions. Su [11] established a bridge construction safety evaluation model based on rough set theory and compared it with a fuzzy analytic hierarchy process to prove the advantages and scientific nature of rough set theory.

To sum up, the current risk assessment methods have been well applied in the field of bridge construction risk assessment, but there are still some deficiencies. Because the bridge construction risk evaluation system involves many risk factors, many scholars conduct evaluation research by establishing the fuzzy comprehensive evaluation method, gray comprehensive evaluation method, analytic hierarchy process, and other methods. However, the complex interference environment risk evaluation of bridge construction is a multifactor comprehensive evaluation problem; there are also artificial subjectivity, complexity, fuzziness, and strong uncertainty of risk factors. Although the aforementioned methods can analyze the direct causes of the accident and identify the important events that caused the accident, the aforementioned methods cannot effectively reveal the deeper potential causes and specific failure modes of the accident. Therefore, it is difficult to achieve a more accurate, efficient, and deeper assessment of bridge construction risk. In recent years, data mining algorithms such as artificial neural network (ANN), support vector machine (SVM), logistic regression, decision tree, random forest, and other algorithms have attracted great attention because they can accurately assess disaster risk and quickly assess disaster loss and have been successfully applied in some risk and disaster assessment studies. For example, Liu et al. [12] evaluated the risk of debris flow in Ya'an city by using the BP neural network based on the data extracted from the occurrence point of debris flow disaster. Li et al. [13] constructed a risk assessment model of water-inrush in a karst cave tunnel based on reliability and the GA-BP neural network. Lin et al. [14] proposed a quantitative evaluation method for karst tunnel water inrush risk based on a variable weight function and an improved cloud model. Phinzi et al. [15] used RUSLE and the random forest algorithm to assess soil erosion risk in the Umzintlava basin in the Eastern Cape of South Africa. Rohmer et al. [16] proposed a microquantile random forest method for rapid prediction of a random marine flood simulator, which was applied to large tidal coastal sites and achieved good results. Chen and Wang [17] transformed the fault tree into a Bayesian network model, established a fall risk assessment model for bridge construction projects, and analyzed and verified the usefulness of the model. Adewole et al. [18] constructed an integrated streaming media framework based on multiple NB and KNN algorithms for spam detection and risk assessment in microblog social networks. Hai-Qing et al. [19] proposed a SVM-based credit risk assessment model for supply chain finance, and through the analysis and comparison of empirical results, they proved that the credit risk assessment model based on a support vector machine is more effective and advantageous than the logistic regression model based on principal component analysis.

It can be seen that these artificial intelligence algorithms have been widely used in flood risk analysis, landslide risk assessment, credit risk assessment, environmental monitoring, and other fields and achieved good results, but there are few reports in bridge engineering disaster risk prediction. As the structural system and construction conditions of bridge engineering are changeable, personnel and mechanical operations are intersected and intensive and there are many uncertain factors and potential hazard sources in the construction process. In order to evaluate the risk of bridge construction in complex interference environments, this paper proposes a risk assessment method for bridge construction based on artificial intelligence (AI) algorithms, such as the random forest algorithm, bagging algorithm, and SVM algorithm and analyzes the effects of these algorithms. At the same time, a real bridge case was evaluated and verified to further verify the effectiveness of the artificial intelligence algorithm for bridge construction risk evaluation.

2. Statistics of Bridge Collapse Accidents in China

According to whether the bridge is put into use, the state of the bridge is divided into the construction period and the operation period. In this paper, bridge collapse accident refers to the collapse or damage of the whole or part of the structure, casualties, and construction equipment damage caused by human error or natural disaster during the construction or operation of the bridge.

According to incomplete statistics [20], in the past three years, there were 26 bridge accidents in the world and 17 serious bridge accidents in China, among which 10 occurred in the construction stage and 7 in the operation stage. According to statistics, there were 9 bridge collapse accidents in Sweden, Italy, and other countries, among which 4 occurred during the construction period and 5 occurred during the operation period. The statistical results of bridge accidents in China are shown in Figure 1.

Figure 1 shows the statistical results of accidents classified by the bridge construction period. The number of accidents in domestic construction period is larger than that in the operation period, while the number of accidents in the foreign construction period is smaller than that in the operation period. The main reason is that China is still in the stage of infrastructure construction, while foreign developed countries have completed infrastructure construction. A total of 52 people died in foreign bridge accidents, including 1 in the construction period and 51 in the operation period. A total of 41 people were injured in domestic bridge accidents, and 80 people were injured in foreign bridge accidents. The Morandi Bridge in Italy alone caused 43 deaths during operation, which shows that bridge collapse caused great harm, and it is very important to analyze and learn the causes of bridge accidents.

As the most important stage of bridge structure, the construction stage has a direct impact on the service life of bridge structure and bridge accidents caused by construction are relatively complicated. As a complex load-bearing structure, bridge structure has many unknown and variable factors in the construction process, which greatly increases the risk of bridge structure destruction.

3. Bridge Construction Risk Assessment

3.1. Random Forest Algorithm. The random forest algorithm is an integration method based on a decision tree proposed by Breiman [21] in 2001. The decision tree is obtained by random sampling training of the training sample set, and the prediction results are obtained by combining the prediction of multiple decision trees through voting. Its functional model is as follows:

$$H(x) = \arg\max_{Y} \sum_{i=1}^{k} I\left(h_i(x) = Y\right), \tag{1}$$

where K is the number of decision trees, Y is the output variable, I is the indicative function, $H(x)$ represents the combinatorial classification model, and $h_i(x)$ represents the classification model of the i-th decision tree.

In the construction of the random forest algorithm, the bootstrapping method was first used to remove m samples from the original training set, and a total of n_tree subsamplings were performed to generate n_tree training sets. For n_tree training sets, n_tree decision tree models are trained, respectively. For a single decision tree model, assuming that the number of features in the training sample is n, the best feature is selected for each split according to the information gain or information gain ratio or Gini index. Each tree continues to split until all the training samples for that node are of the same class. Pruning is not necessary in the splitting process of the decision tree. The multiple decision trees are formed into a random forest. For the classification problem, the final classification result is determined by voting of multiple tree classifiers. For regression problems, the final prediction result is determined by the mean of predicted values of multiple trees, and the algorithm flow is shown in Figure 2.

3.2. XGradient Boosting (XGBoost) Algorithm. XGBoost is one of the boosting algorithms [22], which is an efficient system implementation of gradient boosting. It integrates many decision trees to get a strong classifier. XGBoost is a promotion tree model that has many advantages. It uses a number of strategies to prevent overfitting. Objective function optimization makes use of the second derivative of the loss function on the function to be solved and adds the processing of sparse data. By using cross validation and early stop, construction can be stopped in advance when the prediction results are good and the training speed can be accelerated. Therefore, it is very suitable to evaluate the importance of various indicators.

3.3. Bagging Regressor Algorithm. The bagging algorithm is an integrated learning algorithm, which was first proposed by Leo Breiman in 1994 [23]. It uses a sampling method with fallback to generate training data. Through the random sampling of the initial training set, multiple training sets are generated in parallel, corresponding to the training of multiple base learners, and then, these base learners are combined to build a strong learner. In essence, sample disturbance is introduced to reduce variance by increasing sample randomness. The bagging regressor is an ensemble metaestimator that is a basic regressor that fits on each random subset of the original dataset, aggregating their individual predictions into the final prediction.

3.4. Support Vector Regression (SVR) Algorithm. The support vector machine (SVM) is a machine learning algorithm based on the risk minimization inductive principle for finding the optimal elements in a set [24]. The SVM mainly includes the support vector classifier (SVC) and support vector regression (SVR). SVR was introduced in 1997, unlike traditional statistical regression methods, which rely on the minimum deviation between all training data and predicted data, and support vector regression is based on the minimum error bound of all data. Therefore, support vector regression only requires a subset of training data, which greatly improves computational efficiency and ensures accuracy.

SVR maps data to high-dimensional feature space through kernel function and approaches functions in high-

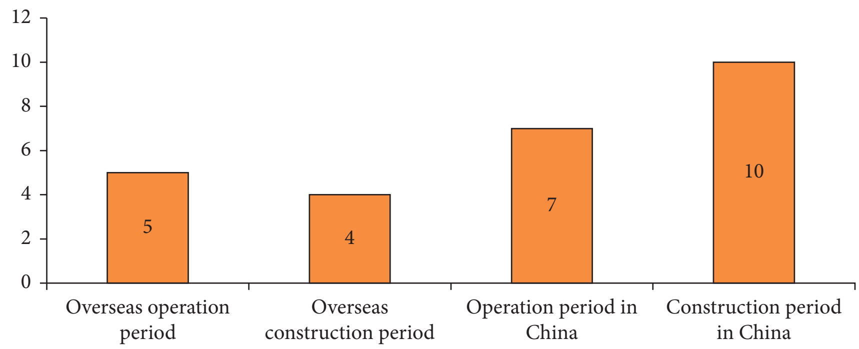


FIGURE 1: Statistical results of bridge accident occurrence stages from 2017 to 2019.

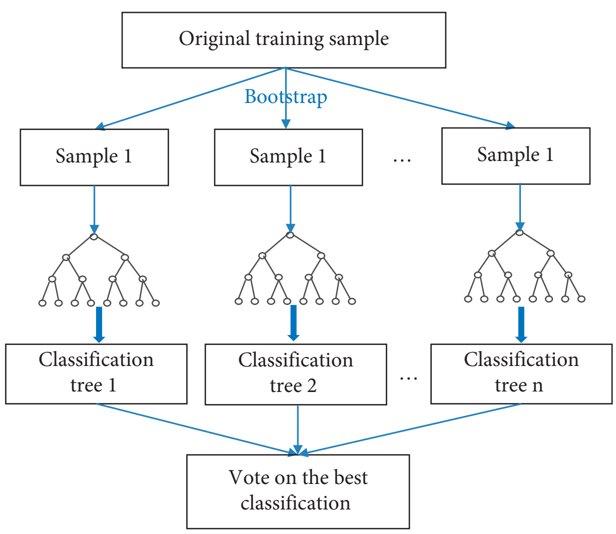


FIGURE 2: The flow chart of the random forest algorithm.

dimensional space by minimizing structural risks. Because only some parts of the vector are relied on the process of model establishment, it is called support vector. The linear regression problem of SVR can be described as follows.

given sample $\{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}$, $x_i \in R^n$ represents the independent variable, y_i is to be predicted, and n represents the number of samples in the learning process. In the SVM model, all the data x in the low-dimensional space can be converted into the high-latitude space F through the nonlinear mapping function φ. The regression function in this process is expressed as follows:

$$F(x) = [\omega \cdot \varphi(x)] + b, \quad (2)$$

where ω is the weight vector and b is the bias term. Namely, suppose the error between the predicted value and the actual output value by fitting function regression is ε and ε^* is the setting error. Ideally all the training sample data can fall in the region of the radius ε^* . However, when the error exceeds ε^*, beyond the part will be punished. In this way, the problem should be optimized to obtain the parameters of the fitting function that minimizes the loss function, i.e.,

$$\begin{cases} \min\left[\frac{1}{2}\|\omega\|^2 + c\sum_{i=1}^{k}(\xi_i^+ + \xi_i^-)\right] \\ y_i - \omega^T x - b \le \varepsilon^* + \xi_i^+ \\ \omega^T x + b - y_i \le \varepsilon^* + \xi_i^- \end{cases}, \quad (3)$$

where C is the penalty coefficient, ξ is the relaxation factor, and among them, the ξ_i^+ is above goal beyond the ε^* part andξ_i^- is under goal beyond the ε^* part. Usually, the actual training sample data do not meet the strict linear ideal conditions; therefore, the nonlinear transformation is mapped to a higher dimensional space for linear processing by introducing the kernel function $K(x_i, x_j)$. Thus, the final regression equation can be solved as follows:

$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)K(x_i, x_j) + b, \quad (4)$$

where a_i and a_i^* are optimization parameters in the dual form in equation (2). The kernel function $K(x_i, x_j)$ is selected according to the characteristics of the data in the sample. The common kernel functions are polynomial kernel function, radial basis kernel function, sigmoid kernel function, and so on.

3.5. Intelligent Algorithm Assessment Process of Bridge Risk. The risk assessment of bridge construction safety using data mining classification technology is divided into two steps: modeling and prediction. Firstly, by analyzing and classifying the risk data of the existing bridge construction, a sample group of attribute categories of the evaluation data flow is established as a training dataset. Here, each risk factor in the data sample is considered as an influence attribute. After that, an artificial intelligence algorithm is used to approximate the comprehensive evaluation value iteratively under the condition of guidance to complete the modeling process. After the corresponding rules are derived, the risk level of the unknown data group can be predicted and the target value of the test sample can be obtained; the grade can be determined according to the classification of the risk level.

The bridge risk assessment process based on the artificial intelligence algorithm is shown in Figure 3.

4. Bridge Construction Risk Assessment Using the Artificial Intelligence Algorithm

4.1. Identification and Statistics of Bridge Construction Safety Risk Factors. Bridge construction is a very complex and systematic work, and there are always risks from construction preparation to completion. These risk factors are hard to spot, and when they do occur, they can have very serious consequences. According to the literature [25], a survey of 500 bridges with accidents in the world found that there were 368 bridge accidents in China, accounting for 73.6% and 132 bridge accidents in foreign countries, accounting for 26.4%. At the same time, the bridge engineering accidents caused by construction only account for 5% in foreign countries and as high as 90% in China, which shows that there is a big gap between the bridge construction management level in developing countries and developed countries.

It can be seen that there are high risks in the construction of bridges in developing countries, and sufficient attention must be paid to them, otherwise engineering accidents are easy to occur; these engineering accidents often cause huge economic losses and casualties and bring adverse social impacts. Therefore, it is the primary task for managers to identify the sources of risk in bridge construction. Through risk identification, the causes of risks are found out and the key risks are judged. Risk identification is the beginning of engineering safety risk management, so effectively identifying safety risk is the most basic requirement of safety risk assessment. The bridge has been accompanied by various risk factors in the whole construction process, and according to the above bridge accident investigation and analysis, the risk of engineering structures, especially Chinese bridges, is much higher during the construction period than during the service period.

According to the above bridge accident investigation, the collapse of bridge construction is mainly caused by many unfavorable factors. In view of the characteristics of bridge construction, according to the above literature [25], bridge construction-related accidents are collected, and risk accident types are obtained that are summarized in Table 1. At the same time, the cause theory of an accident is used to analyze the cause and development of the accident, and the loss caused by the accident is counted.

Through the analysis and summary of the above risk factors, the 4M1E [26] method in the project construction quality management system is introduced to classify risk factors into five types: men, machine, material, method, and environment. In this way, the index system of bridge construction safety risk assessment can be established by the 4M1E method.

4.2. The 4M1E Method of Risk Analysis and Classification of Bridge Construction. In order to solve the subjective problem of risk identification and quantification, a novel idea of risk characterization by quality parameters is put forward. Since quality and risk are two sides of the coin, risk and quality management systems are intertwined, and quality feature identification can be used to identify and quantitatively assess risks. In the practice of quality management, factors that measure the level of quality can be divided into five categories: man, materials, machines, methods, and environment, namely, 4M1E.

Figure 4 illustrates the linkage mechanism among risk factors, risk environment, and risk loss. This classification of quality factors has been widely used within the framework of quality management [27]. Therefore, factors in risky construction can also be divided into 4M1E and evaluated accordingly. Some scholars have attempted to adopt the 4M1E framework in risk assessment [28].

In the work, four factors including man, machine, material, and method should be fully considered. Besides that, 1E should also be included. So it is collectively called 4M1E. Men are the focus of all management theories and the biggest difficulty in engineering project management.

According to statistics, natural disasters only account for 2% of numerous accidents, that is; 98% of accidents can be prevented within the scope of human ability [29]. Machine refers to mechanical equipment used in engineering construction. Bridge engineering needs to use many large pieces of mechanical equipment, the quality of equipment will affect the quality of construction. Under normal construction conditions, if the mechanical equipment cannot meet the requirements of construction accuracy, the construction quality will not be guaranteed.

On the other hand, if the mechanical equipment is poorly managed, causing damage to the equipment, it will directly affect the construction process. Therefore, it is extremely important to select and properly maintain the machinery before construction. Material refers to engineering materials. Material quality plays an important role in engineering quality. If the material quality does not meet the construction standards, even if the construction quality control is well performed, there will still be engineering quality problems.

For bridge engineering, there are many kinds of materials and large amounts of consumption. If there is a problem with one material, it will have a significant impact on the whole project. Therefore, the quality control of engineering materials is an important guarantee to improve the quality of engineering. Method, in engineering project management mainly refers to the construction method. An innovative engineering project often uses many innovative construction methods because the use of these methods can solve a particular engineering problem, and this reflects the importance of construction methods. In order to achieve the same quality goal, if the appropriate method is chosen, the economic benefit will be greatly improved, while the project progress can be guaranteed.

Construction affiliate in the selection of construction methods should combine with the actual consideration of all aspects of the project and try to work out the best construction method in an economical way. There are many environmental factors affecting the quality of engineering

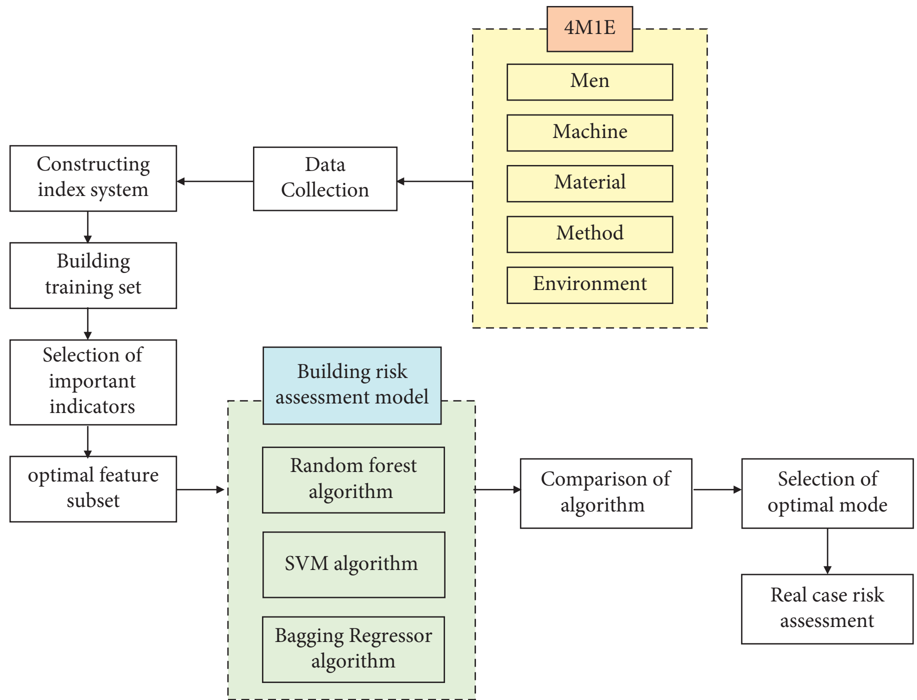


Figure 3: Bridge construction risk assessment process.

Table 1: Main risk factors of bridge construction safety.

Serial number	Risk factor	Recognition methods
1	Quality problems of reinforcement engineering	Accident summary
2	Quality problems of concrete engineering	Accident summary
3	Foundation engineering accidents (foundation settlement, foundation frost heaving, insufficient bearing capacity, etc.)	Expert survey
4	Uneven casting of box girder roofs	Expert survey
5	Local cracking of concrete in anchorage zones	Expert survey
6	The deviation of stretching elongation of prestressed tendon is too large	Expert survey
7	Failure of prestressed tensioning equipment	Expert survey
8	Sliding and broken wires of prestressed tendons	Expert survey
9	Cracking of the bottom slab during prestressing	Structural analysis
10	Improper operation of operators	Expert survey
11	Improper operation of lifting machinery	Expert survey
12	Formwork deviation during concrete casting	Expert survey
13	Failure of construction support and collapse of scaffold	Accident summary
14	Improper installation and removal of formwork	Accident summary
15	Removal of tower crane, gantry, and other temporary equipment	Accident summary
16	Unqualified height difference of the closure section	Accident summary
17	The casting quality of box girder roofs is unqualified	Expert survey
18	Accident of hanging basket walking	Expert survey
19	Accident during removal of the hanging basket	Accident summary
20	Collapse of bored piles	Expert survey
21	Slurry leakage during drilling	Expert survey
22	The elevation of reinforcement cage is unqualified	Expert survey
23	Accidents of electric shock, fire, and container explosion at construction site	Accident summary
24	Mechanical injury accident at construction site	Accident summary
25	Falling accidents of construction workers	Accident summary
26	Accidents caused by wind, rainstorm, flood, high temperature, fog, etc	Site survey
27	High altitude falling in cantilever pouring construction	Accident summary
28	Impact of construction on safety of surrounding residents	Accident summary
29	Impact of construction on environment	Site survey

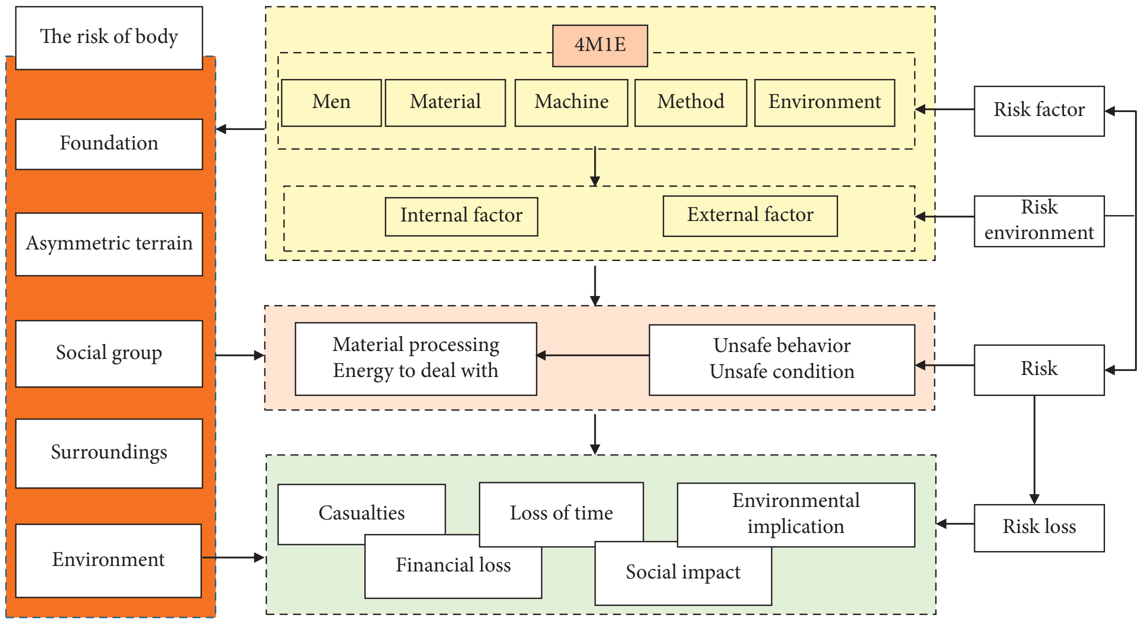


FIGURE 4: The construction risk mechanism based on 4M1E.

projects, which are complicated and changeable. The most typical construction environment is the meteorological environment. Extreme weather conditions can lead to delays in construction time, reduced project quality, and other conditions. The meteorological environment is the most uncontrollable of all the control factors, so the construction personnel should fully consider the local climate conditions when making the construction plan, arranging the construction period reasonably, and trying to avoid conflicts with the bad weather.

It can be seen that bridge construction needs to comprehensively consider the five influencing factors of engineering quality combined with these factors and the actual characteristics of the project to develop the construction plan. Therefore, on the basis of fully identifying the risk factors in the bridge construction stage, this paper tries to summarize the bridge construction safety risk assessment method based on 4M1E by combining the expert investigation method and the 4M1E method.

4.3. Index of Risk Assessment for Bridge Construction. Bridge construction is divided into many stages; each stage has different conditions, and some of which are controllable projects and some are uncontrollable projects, according to the uncertainty of the project to define whether it is a risk project. According to different aspects of the bridge construction stage, bridge structure, and bridge construction control content, the risk of bridge construction is divided into units and each risk factor is classified under each unit.

However, under the influence of many factors such as different bridge types and different construction environments, it is almost difficult to take every risk into account. If too many factors are considered, the consideration of the main factors will be affected and the analysis will be difficult. Therefore, it is very important for modeling to establish a reasonable data group or data warehouse with strong usability by selecting appropriate indicators. As a result, in view of the complexity of the bridge construction environment, the identification of the interval of various influencing factors may be fuzzy. Based on engineering practice and expert experience [30], this paper uses 4M1E to finally determine the risk evaluation index system of the bridge construction stage, as shown in Table 2.

The first layer is the target layer, and the second layer is the criterion layer, which is the source of risk that may lead to the risk in the bridge construction stage. The third layer is the index layer, which contains 26 index factors. The importance and coverage of these index factors are fully considered, and the indexes with greater relative influence on the risk are selected to minimize the intersections between the indexes so as to comprehensively measure the various risk factors affecting the bridge construction. In order to facilitate screening of attribute indexes that have a greater impact on risk, all attribute indexes are numbered.

Risk level is the indicator of evaluating the risk of bridge construction. For the risk level determined by semiquantitative indexes, the risk level can be expressed by data and its interval. According to "The Safety Risk Assessment Guide for Highway Bridge and Tunnel Engineering Construction" [31], the risk levels of bridges are divided into super risk, high risk, moderate risk, and mild risk, which are, respectively [1.0,0.8,0.4,0.2], as shown in Table 3.

4.4. Index Importance Analysis and Screening Optimization. According to the established bridge construction risk assessment index system, relevant data of bridge construction risk factors collected in the existing literature [25] are adopted and used as the training and testing sample space of the artificial intelligence algorithm. There are many risk modes and related risk factors initially identified, but not all

Table 2: The index of risk assessment for bridge construction safety.

Level 1 (target level)	Level 2 (criterion level)	Level 2 (index layer)
Construction safety risk of complex overpass	Personnel risk	Worker experience ($F1$) Technician experience ($F2$) Project manager experience ($F3$) Rationality of organization ($F4$) Communication and coordination among project participants ($F5$)
	Material science	Steel ($F6$) Grouting material ($F7$) Composite ($F8$)
	Equipment	Equipment maintenance ($F9$) Matching degree of equipment ($F10$) Update and replacement of equipment ($F11$) Mechanical failure rate ($F12$)
	Theory	Maximum span of single span of the bridge ($F13$) Number of structural system changes ($F14$) Complexity of bridge structure ($F15$) Geological exploration ($F16$) Traffic flow ($F17$) Control degree of construction quality ($F18$) Safety production education ($F19$) Monitoring and emergency treatment ($F20$)
	Environment	Working environment ($F21$) Soil mass ($F22$) Rock quality ($F23$) Basic wind pressure ($F24$) Probability of abnormal wind Seismic intensity grade ($F26$)

Table 3: Grade of risk assessment and requirements of the bridge.

Risk index	Risk level II	Requirement
0~0.2	Mild risk	The risk level is acceptable, the current response measures are effective, and it is not necessary to take extra preventive measures
0.2~0.4	Moderate risk	The risk level is conditionally acceptable, and further preventive measures are necessary to be taken to improve safety
0.4~0.8	High risk	Risk levels are conditionally acceptable, risk mitigation responses must be implemented, and contingency plans need to be prepared
0.8~1.0	Super risk	The risk level is unacceptable, and effective countermeasures must be implemented to reduce the risk level below M; if the cost of coping measures exceeds the owner's ability to bear, then change the program or abandon the project implementation

of them are of great importance to the analysis object. Too many risk factors will lead to redundant information, which will adversely affect the establishment of the model. Therefore, feature screening requires identifying risk patterns and related risk factors that are highly relevant to the research content and retaining factors with high importance.

First, the XGboost algorithm under scikit-learn was used for calculation, and the ranking of feature importance of indicators was obtained, as shown in Figure 5. The technical level of personnel, communication, and coordination of project participants and change times of the bridge system, geological conditions, and the equipment matching degree are relatively high, indicating that these indicators have a great influence on risks. However, the importance and influence of seismic intensity, abnormal wind probability, rationality of organization and grouting materials are relatively low, which is basically consistent with the actual situation. Considering the small size of the sample dataset, the feature indexes in the last few places were removed. A total of 14 indicators with thresholds greater than 0.028 were selected as training sample indicators for subsequent modeling.

4.5. Comparison of Accuracy of Risk Assessment Models. In order to verify the validity of the model, SVR and bagging regressor algorithms that were suitable for regressive analysis were selected for comparative analysis in the same experimental environment. And models were built for comparison. The mean square error (MSE) and goodness of fit R^2 were selected to determine the accuracy.

The goodness of fit refers to the degree of fit between the model and data. The value ranges from 0 to 1, and the closer

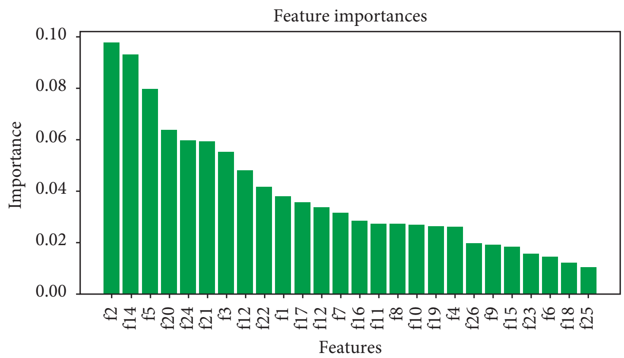


Figure 5: Ranking of importance of indicators.

it is to 1, the better the effect is. The smaller MSE is, the better the model effect is. RSS is the sum of the squares of residuals. The smaller RSS is, the better the effect of the model is. The calculation formula refers to equations (5) and (6), and the error results are obtained by comparing the errors of the three prediction models, as shown in Table 4.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(f_i - y_i\right)^2, \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - f_i\right)^2}{\sum_{i=1}^{N}\left(y_i - \hat{y}\right)^2}, \tag{6}$$

where N is the number of samples, i is each data sample, f_i is the predicted value of the model, y_i is the actual numerical label of the sample point I, and $\hat{y}$ Is the average of real value tags. Compared with the running results, the SVR model has the lowest prediction accuracy and larger error. The bagging regressor model had the smallest mean square error (MSE), but the model was not very stable, and the results varied greatly from time to time. The prediction result of the random forest model is most close to the actual value, with a higher precision and better effect. In order to further understand the reliability and accuracy of the random forest algorithm, the RF algorithm is used for further modeling and prediction of an engineering example.

5. Engineering Application

5.1. Case Example. According to the original design, the FIU bridge is a cable-stayed bridge with a prestressed concrete truss girder, with a total length of 98 m, as shown in Figure 6. The main span and side span of the main beam are 53.3 m and 32.9 m, respectively. The bridge has adopted rapid bridge construction technology and is designed to last 100 years and can withstand hurricanes of category 5. Under the action of the construction load, the inclined belly bar 1 losses its compressive capacity and leads to the continuous collapse of footbridge.

5.2. Risk Analysis and Assessment. A number of Chinese and foreign experts conducted in-depth analysis on the causes of FIU bridge collapse, looking for reasons from various

Table 4: Precision comparison of the three algorithms.

Algorithm	Actual value	Predicted value	Performance indicators		
			R^2	MSE	RSS
RF	0.412	0.396	0.9115	0.0012	0.0126
SVR	0.412	0.379	0.6240	0.0068	0.0686
Bagging regressor	0.412	0.387	0.9473	0.0010	0.0102

aspects such as material problems, support conditions, stress testing, design and construction problems and concluded that the accident was the result of a combination of multiple factors. In order to test and analyze the accuracy of the method in this paper, relevant data before the accident were collected. Based on the above risk assessment indicators and data, the data results of each indicator are normalized as follows:

$$\begin{pmatrix} 0.617,\ 0.732,\ 0.612,\ 0.72,\ 0.5,\ 0.613,\ 0.514, \\ 0.72,\ 0.516,\ 0.732,\ 0.867,\ 0.75,\ 0.579,\ 0.562 \end{pmatrix}. \tag{7}$$

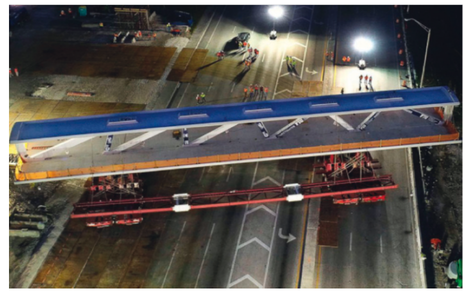
From the above comparative analysis of the RF, SVR and bagging regressor intelligent algorithms, the prediction results of the random forest model is most close to the actual values, with a higher precision and better effect. In order to further understand the reliability and accuracy of the random forest algorithm, the RF algorithm is used for further modeling and prediction of the actual engineering case, that is, the FIU bridge. The normalized data were input into the random forest model which was previously established, and the calculated risk result was 0.56, which was classified as high risk according to the risk level.

On March 15, 2018, the main span of the footbridge at Florida International University (FIU) collapsed, as shown in Figure 6(b) (global focus 2018). According to the risk assessment level, the collapse of the bridge belongs to high risk, and the risk assessment result of the method in this paper also belongs to high risk, which is basically consistent with the actual risk of the bridge. Due to the lack of effective risk control and risk transfer in the construction process, the bridge eventually collapsed in the construction process. It can be seen that the artificial intelligence algorithm can effectively carry out risk assessment and prediction.

5.3. Discussion. In order to evaluate the degree of each structural reliability index, this paper adopts the XGBoost method in sklearn to evaluate the influence degree of each indicator. The influence degree of each factor on the risk assessment of bridge structure is quantitatively judged. Taking into account the influence degree, economy, and applicability of each factor comprehensively, the indexes that have little influence on the prediction results are eliminated.

There are various artificial intelligence algorithms used for predictive evaluation. This paper compares the risk prediction of three kinds of regression algorithms in machine learning methods and concludes that the prediction effect of the random forest algorithm is better. At the same

(a)



(b)

Figure 6: The actual scene diagram and collapsed scenario of the American FIU bridge. (a) A rendering of the FIU human bridge. (b) The FIU bridge construction collapse site.

time, this method avoids the artificial factors in the process of evaluation and greatly improves the accuracy. However, this method requires a sufficient number of samples and a very similar construction process; meanwhile, training samples need to be carried out in recent years so as to ensure the accuracy and rationality of the results. Due to space and time, not many samples have been collected. Further studies are required that will investigate and sample more and more sufficient examples to obtain a more reasonable and scientific mapping relationship between input and output indicators.

The treatment measures of general risk sources studied in this paper are relatively simple, which can be precontrolled and early warning according to general measures, thus reducing the uncertainty of its occurrence. After the risk assessment, the risk level of each major risk source is obtained and further measures are required in accordance with the risk acceptance criteria. The weak links are identified where construction risks occur, failure modes are summarized, and specific suggestions are received to avoid problems in bridge construction.

6. Conclusions and Future Development

In recent years, although a large number of research achievements have been accomplished in the theory of bridge engineering structural design, there are still uncertain factors in the process of bridge construction management, such as structural parameters, load parameters, and the uncertainty caused by the limitations of the people's understanding level. It is because of these uncertain factors and some engineering technology factors that the construction risk of bridge construction is inevitable. At present, scholars around the world have carried out a wide range of studies on risks in the chemical industry, environmental protection, aerospace engineering, medical and health, and economic fields and achieved good results. However, it is only in recent years that the structural risk analysis of civil engineering, especially bridge engineering, is deeply studied, and there are still many problems to be further discussed and studied.

As the structural system and construction conditions of bridge construction are changeable and uncertain, it is difficult to achieve rapid and accurate risk assessment in the process of bridge construction. In this paper, the 4M1E analysis method is used to analyze and classify the risk factors affecting the construction stage of the bridge and the artificial intelligence algorithm and the evaluation process of the bridge risk are proposed. The risk assessment model for bridge construction is constructed by typical artificial intelligence algorithms such as the support vector machine (SVM), random forest (RF), and bagging regressor. The accuracy of the typical artificial intelligence algorithm model is compared and analyzed, which shows that the random forest algorithm has more advantages in efficiency and accuracy.

In order to further verify the applicability and accuracy of the artificial intelligence method, the random forest algorithm is used to analyze and verify the construction example of the FIU bridge, and the results obtained are basically consistent with the risk assessment results of the FIU bridge, which further verifies the feasibility and effectiveness of the method. Therefore, the artificial intelligence algorithm can analyze and evaluate the bridge construction risk more efficiently and accurately, and it is proved to be useful to realize the rapid and accurate analysis and evaluation of the bridge construction risk by using the random forest algorithm.

Through the research of this paper, in order to realize the rapid assessment of bridge construction risk, it is necessary to investigate and collect bridge accidents and establish a perfect bridge engineering accident database. At present, China has not established a complete set of the bridge engineering accident database. Through the establishment of the database and the analysis of the accident data in the database, we can understand the causes and general rules of the accident, reveal the mechanism of the accident, and predict the possible consequences of the accident. These research studies have important guiding significance for improving bridge design, strengthening bridge protection and management, and avoiding bridge accidents.

The results of different intelligent algorithms will directly affect the accuracy and quality of risk assessment. Therefore, research on the applicability and accuracy of different algorithms should be strengthened. In addition, intelligent algorithms can learn from raw data. If there is a complete security dataset, a subjective intelligence algorithm model can be built. Furthermore, the risk of accidents caused by other different causes in bridge construction engineering, such as instability, collision, electric shock, falling, and being hit by falling objects, can be widely applied to the intelligent algorithm to cover the comprehensive safety diagnosis and strengthen safety management to reduce bridge construction site construction hazards. It can be predicted that with the rapid development of artificial intelligence technology and the high integration of the artificial intelligence algorithm and bridge construction, it is bound to provide effective solutions for risk assessment in all stages of bridge construction, even operation and maintenance.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors gratefully acknowledge the financial support provided by the Science Foundation of China Postdoctor (Grant no. 2016M600352), the Science and Technology Agency of Zhejiang Province (Grant nos.. 2015C33222 and LGF19E080012), and the Science and Technology Project of Zhejiang Provincial Department of Transportation (Grant nos. 2019H14 and 2018010). The authors are grateful to the Jiaxing Science and Technology Bureau of China under Grant (2021AY10043) and the Project Supported by Scientific Research Fund of Zhejiang Provincial Education Department (Y202147784).

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