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Risk Management for Housing and Construction Projects

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Abstract: Housing building projects require careful project management because of their lengthy lead times, significant investment requirements, and high-risk nature. Aimed at effective management and risk assessment of engineering project construction, a risk management model for the entire process of project engineering is established. Risk information on engineering construction projects is obtained through case studies and relevant literature data, and key risk factors are screened using big data technology. Considering the complexity and nonlinearity of risk factors in engineering project construction, a feedforward model (BP) is adopted to solve the risk management model and achieve project risk prediction. Meanwhile, considering that traditional BP models are affected by initial parameters during the training process, they are prone to local convergence problems. Innovatively introducing a Sparse Search Algorithm (SSA) to optimize the construction of the SSA-BP engineering risk prediction model, achieving project risk management and evaluation. In the risk level prediction of risk factors, the Particle Swarm Optimization-Back propagation (PSO-BP) has a large error from sample 15 to sample 30, and the average prediction accuracy of the risk factor level is 73.65%, while the average prediction accuracy of SSA-BP model is 92.65%. In the project risk factor prediction, the average prediction accuracy of the SSA-BP model and PSO-BP model are 91.68% and 82.69%, respectively, which shows that the SSA-BP model has better risk management ability. The SSA-BP model exhibits higher precision and accuracy, improving the ability of engineering project risk management. In addition to offering trustworthy tools and procedures for decision-making in linked sectors, research provides a significant technical reference value for risk management in building projects.

Keywords: Case study, building construction, construction projects, risk management, sparrow search algorithm (SSA), backpropagation (BP), particle swarm optimization-back propagation (PSO-BP).

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1. Introduction

Construction engineering has ushered in rapid development in recent years as well as great achievements in the Chinese industrial output value and livelihood economy. Construction engineering has developed into a foundational business in China, according to pertinent statistics. More than 50 million people are employed in the construction business, which is supported by many different disciplines, and the risk management of construction projects is crucial to the growth of the entire sector (Taofeeqet et al., 2020). Project risk management faces various challenges since it is impacted by market factors, human factors, technological constraints, cost considerations, and other elements in the real world. To effectively manage the entire process risks of construction projects and avoid risk issues during construction, case study methods are introduced into the entire process risk management of projects to improve the effectiveness of project risk management. By evaluating representative events and collecting data across the entire event range, case study methods are used to derive relevant guidance from specific cases, providing important judgment foundations for decision-makers (Qazi and Dikmen, 2019). The management focus and challenges of engineering projects can thus be more precisely reflected through the research of typical examples in engineering project risk management and the creation of a project whole process risk management model mining and analyzing engineering data. To achieve the project's overall process risk control, the entire construction process, including the construction technique, equipment, employees, and materials, must be examined throughout the real risk management phase. Due to the complexity of risk management in construction projects, a BP neural network is introduced to solve the risk model. At the same time, the sparrow search algorithm is used to optimize the BP model and construct the SSA-BP model solution model, thereby achieving the monitoring and management of hazards in construction projects. This enables the monitoring and management of hazards in construction projects. The proposed method has good application effects in building risk assessment, and the research content offers crucial technical references for risk management and construction management of construction projects, according to the data results.

2. Related Works

Case studies can offer useful management guidance for construction risk management in the sector of building construction, where the complexity and specialization of construction expose the entire process to many hazards.（Yoshikawa et al., 2020) investigated current construction risk issues and discovered that case studies and quantitative analysis might offer crucial guidance for engineering projects. As a result, to evaluate project risk and apply it to the field of wood building safety in the Canadian region, quantitative loss estimates, and related case studies were used. The analysis's findings demonstrated that the suggested technique was successful in identifying risk issues and offering reliable project construction advice (Brill and Robin,2020). In their analysis of the state of construction risk management, (Baradan et al., 2022) note that the interdependence of project interests creates numerous hazards throughout project construction. By reviewing pertinent cases, using information modeling techniques to create a matrix of components, and evaluating the success of the strategy in particular situations, the goal is to lower the risks. The suggested solutions have been thoroughly examined, and they effectively monitor construction risk (Rehman et al., 2022). Several structures had issues with overheating concerns, according to an analysis of building failure analysis techniques done by (McLeod et al., 2020). Then, using pertinent case data, the corresponding data models for the building scenarios were created. Models are used to replicate current construction risk issues. The final results demonstrate the effectiveness of the suggested strategy in predicting construction hazards and in offering building designers useful management guidance (McLeod et al., 2020). In a study on construction hazards in building projects, (Andersson et al., 2019) found that a project's risk management is significantly influenced by the organizational process of project construction. Therefore, to find useful guidance on organizational management, the organizational characteristics of construction were examined, as well as the characteristics of the various risk factors within the organization. The results demonstrate that the approach is good for streamlining organizational management procedures, preventing the occurrence of unforeseen occurrences, and successfully advancing the construction process (Andersson et al., 2019).

The effectiveness of construction risk management is increased by the use of information processing technologies. The effectiveness of construction risk management is greatly increased by information processing technology, according to a study on the subject by (Hasanpour et al., 2020). The field of underground project construction risk management was then addressed using an Intelligent Algorithm Model Combining Artificial Neural Networks and Bayesian Networks, and a project risk management model was developed by examining project case data. Specific cases were used to apply the model, and the cases were used to compare the effectiveness of the analysis method. The results demonstrated that the suggested technique is more effective at managing risks than other ways, which can better prevent project construction risks (Hasanpour et al., 2020). It can reasonably assess project risks caused by changes in project parameters. A study of the resource management process in construction projects by Bai et al. (2021) showed that poor resource management can have an impact on how resources are allocated and increase project management risks. The goal was to better manage risks brought on by competing project resources. After that, a risk management model for multi-project resources was built using analysis of existing project case data. The model investigates the numerous project construction influencing factors and develops risk indicators using correlation characteristics. To estimate the risk of project building, the risk data is additionally processed using a machine learning model. The proposed model has successfully monitored the complete project process in experimental tests, optimizing the project's overall process goals and preventing projects from encountering risky issues. Bai et al. (2021) and Jiang et al. (2020) stated that construction costs are an important component of construction projects and have a significant impact on project construction. The focus of the research is on the application of backpropagation (BP) neural networks in building cost estimation. Firstly, the influencing factors of construction costs were analyzed. Six factors were selected as inputs for the estimation model. Then, a BP neural network estimation model was established and trained with ten samples. Through implementation analysis, it is shown that the estimation accuracy of this model is higher, has the lowest average error, and has good application effects in construction engineering (Jiang, 2020).

According to the above research, risk management throughout the entire construction process is one of the important aspects of engineering construction, which is affected by environmental and construction factors, resulting in many difficulties in risk management. The above literature has conducted relevant research and discussion on engineering construction risks, but in practical application, there are still problems, such as inaccurate evaluation and inaccurate model construction. In this regard, the case analysis method is used to investigate project management risks. Considering the complexity of risk factors, the use of intelligent algorithms to process risk data can effectively improve the effectiveness of construction risk management and provide an important reference for the control of construction risk control.

3. Risk Management Model for the Entire Process of Engineering Project Construction

3.1. Construction of a Risk Management Model Based on Case Studies

Long construction cycles, complicated task kinds, and high investment are characteristics of construction projects, and these characteristics create several risk factors throughout the management of the entire project. The numerous engineering project risk elements interact with one another at the same time, posing significant management issues for the entire process. To create a risk management model, engineering project instances are therefore mined and studied to uncover the risk components of the entire project construction process. Fig. 1 depicts the project's overall risk management framework (Liu et al., 2022).

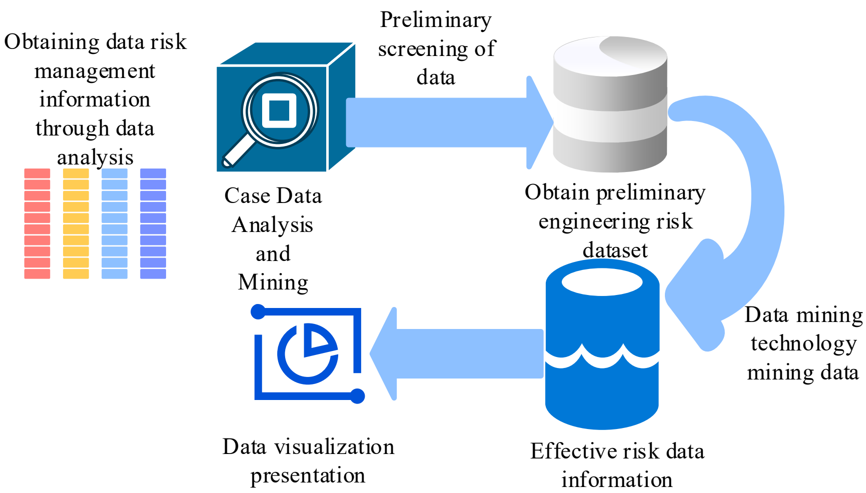


Fig. 1. Project whole process risk management system (adopted from Liu et al., (2022))

The database system, the data identification system, and the data mining system are the three primary parts of the whole risk management system. Project cases, which include a substantial amount of project risk management case data, make up the majority of the database system. The data mining system is utilized to create a project management risk characteristic system after the identification system discovers various types of project risk elements (Feng and Qu, 2022). Considering the numerous factors that affect engineering construction and their uncertainty and hierarchy, the study mines the data on construction risk features using the hierarchical fuzzy approach. Due to the ambiguity and confusion surrounding construction project risk factors, it is necessary to split the risk factors extracted from the instances and establish the significance of the indicator variables based on their level of influence on the risk relevance. Therefore, according to the engineering monitoring quality standards, the hierarchical molecular method was used to mine the main factors. Table 1 shows how to rank the indicators based on their importance.

Table 1. Explanation of index importance scale

Importance Scale	Rule requirements
1	The comparison between factor A and factor B shows that the importance of both factors is consistent
3	Comparison between Factor A and Factor B, factor A is more important than Factor B
5	Compared with factor B, factor A is more important than factor B
7	Compared with factor B, factor A is more significant than factor B
9	Comparison between Factor A and Factor B, factor A is more important than factor B
2,4,6,8	Compare factor A with factor B, take the middle value

The relevance of indicators fluctuates between levels in risk indicator mining, and there is interaction between the different levels of indicators (Nimrah and Saifullah, 2022). Each factor's significance must be evaluated by building a judgment matrix using expert scoring and contrasting factors with target relevance. In Eq. (1) (Yeom et al., 2020), the one-factor judgment matrix is displayed.

$$B = (b_{ij})_{n\times m} \tag{1}$$

Between the matrix elements B_j B_i and, b_{ij} indicates the significance of the A-rated risk factor comparison, and $n\times m$ indicates the number of matrix rows and columns. To create the new matrix shown in Eq. (2), the matrix parameters are regularized.

$$\overline{B} = \overline{b}_{ij} = \frac{b_{ij}}{\sum_{i=1}^{n} b_{ij}} \tag{2}$$

Each row $\overline{B}$ in Eq. (2) must be added to determine the risk factor's weight W_i, and Eq. (3) shows the vector of the risk factor's distinctive indications.

$$W = [W_1, W_2, ..., W_n]^T \tag{3}$$

Eq. (3), $W_1, W_2, ..., W_n$ denotes the weight of each indicator, and the weight of a single indicator is calculated as seen in Eq. (4).

$$W_i = \frac{1}{n}\sum_{j=1}^{n}\overline{b}_{ij} \tag{4}$$

The next step requires the calculation of the maximum characteristic input to the single-factor judgment matrix, as seen in Eq. (5).

$$\lambda_{\max} = \sum_{i=1}^{n}(\frac{(BW)_i}{nW_i}) \tag{5}$$

The judgment matrix consistency must be determined to determine the project construction risk factors, and when the matrix satisfies the consistency standards $\lambda_1 = \lambda_{\max} = n$, the remaining characteristic roots are calculated as 0 (Lu and Zhang,2022). Eq. (6) shows how to find the remaining characteristic roots when the matrix does not satisfy the constraints,

$$\sum_{i=2}^{n}\lambda_i = n - \lambda_{\max} \tag{6}$$

When the criteria are not satisfied, the matrix characteristic roots are modified, and the discriminant matrix must be examined to determine matrix consistency (Yeom et al., 2020). The level of significance is evaluated, as shown in Eq. (7), for other characteristic roots that were calculated to produce a negative mean and satisfy the criteria of the determination matrix.

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{7}$$

The matrix consistency lowers and vice versa, the greater the matrix consistency, according to Eq. (7), where CI denotes the indicator important parameter and CI $\lambda_{\max}$ denotes a positive connection. The project construction of various types of risk collection can then be determined according to the determined risk indicator factors. Through the fuzzy theory screening of the final indicator factors, the target layer corresponding to the risk indicator weight set Eq. (8) is then visible (Afzal et al., 2021).

$$W = \{W_1, W_2, W_3, W_4 W_5\} \tag{8}$$

$$W_i = \{\omega_{i1}, \omega_{i2}, \omega_{i3}, ..., \omega_{in}\} \tag{9}$$

The set of criteria layer weights is set to $W_i = \{\omega_{i1}, \omega_{i2}, \omega_{i3}, ..., \omega_{in}\}$ based on the outcomes of the collation of the target layer weights. Eq. (9) shows the evaluation vector for the criteria layer indicator.

$$W_i = \{\omega_{i1}, \omega_{i2}, \omega_{i3}, ..., \omega_{in}\} \tag{10}$$

Eq. (10), R_i denotes the affiliation of risk factors at the criterion level and the target level evaluation vector, as seen in (11).

$$V = W \cdot R \tag{11}$$

Eq. (11), R denotes the affiliation of the target-level risk factors. The target level risk factors are scored against the criterion level risk factors, as seen in Eq. (12).

$$\begin{cases} T_i = V_i \cdot D^T, (i, j = 1, 2...) \\ T_{ij} = V_{ij} \cdot D^T, (i, j = 1, 2...) \end{cases} \tag{12}$$

Eq. (12), D denotes the corresponding set of building construction risk factor evaluation levels, as seen in Eq. (13).

$$D = \{D_1, D_2, D_3, D_4, D_5\} \tag{13}$$

Eq. (13), D_1, D_2, D_3, D_4, D_5 corresponds to the five levels of risk evaluation from low to high, corresponding to a score of 0 to 5. Building construction is rated as $0 \le T_i \le 1$ when there is low risk $1 \le T_i \le 2$ when there is low risk, $2 \le T_i \le 3$ when there is high risk, $3 \le T_i \le 4$ $4 \le T_i \le 5$ and when there is level high risk (Meharie et al., 2022). The selected risk factors were evaluated by an expert group, and the final risk management evaluation system for the entire construction project process is shown in Fig. 2.

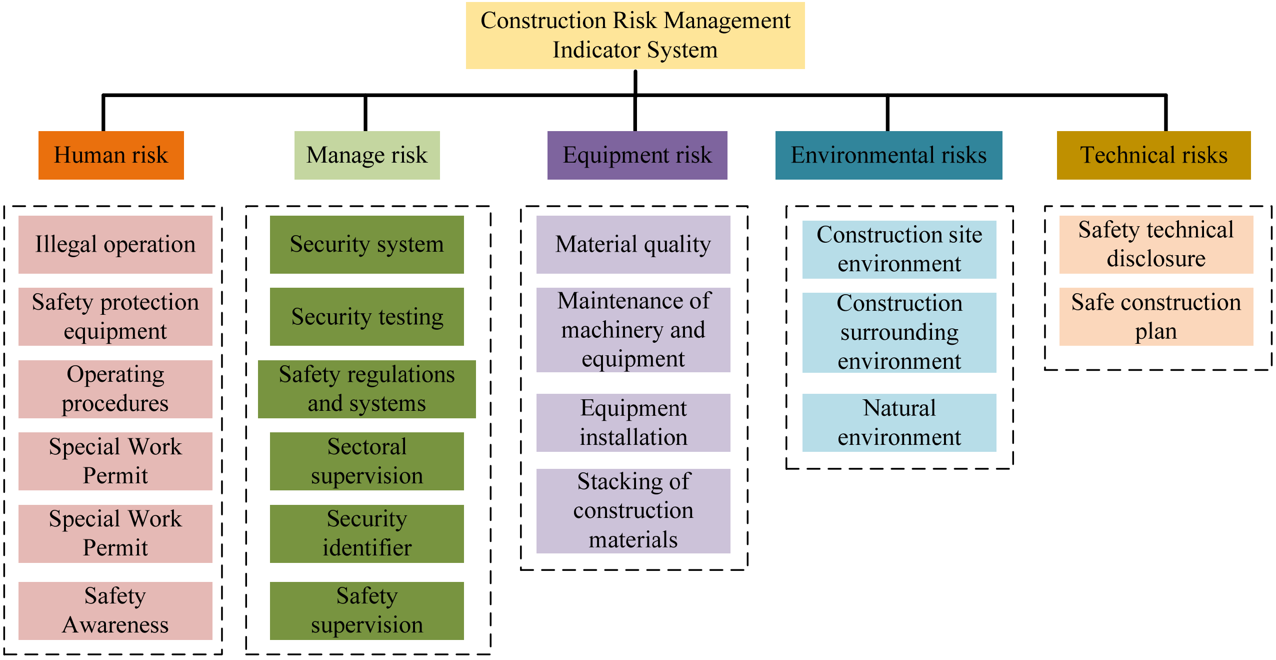


Fig. 2. Risk management indicator system for the whole process of construction projects

3.2.SSA-BP Engineering Risk Prediction Model Construction

The primary project construction process risk elements are weeded out through the mining of engineering project risk cases. The BP model has shown good performance in dealing with complex nonlinear problems, so it is introduced to solve the problem. In Fig. 3, which depicts the structure of the BP risk management model (Jiang et al., 2021), three levels of results—hidden, output, and input—are used to describe the structure of the BP model.

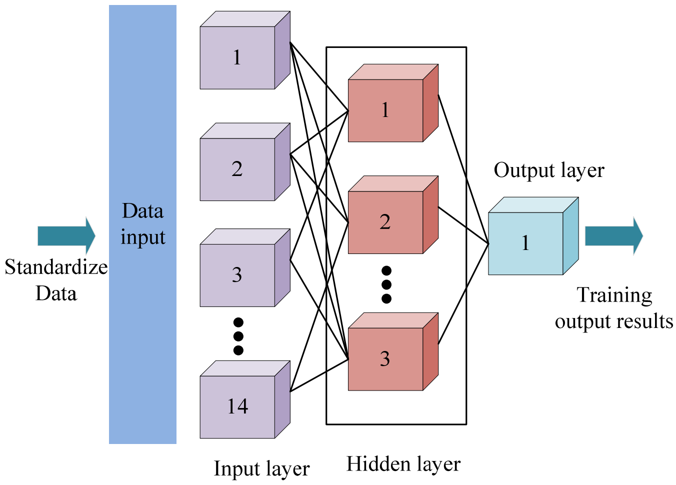


Fig. 3. BP risk management model structure

The mined project risk data is employed as the model's input signal in the BP risk management model, passing successively via the implicit and output layers (Lin and Fan, 2019). To increase the model's training accuracy, the starting parameters must be modified during the data training by the model's training error. The indicated layers must be used to map the nonlinear data of the construction risk variables. The ultimate training effect of the data is influenced by the number of implied layers, which is determined using an empirical formula, as shown in Eq. (14) (Bai et al., 2021).

$$k = \sqrt{l + m} + a \tag{14}$$

l, m a and in Eq. (14), respectively, stand for the number of neurons in the input, implicit, and output layers. These have a range of values between 1 and 10. For the researcher to choose the appropriate model training structure, the empirical Eq. is inserted into the model training process. However, in practice, conventional BP models are sensitive to the initial parameters and experience local convergence issues while being trained. To optimize the initial parameters of the BP model and enhance the model's training effect, the Sparrow Search Algorithm (SSA) is implemented. The optimization search principle of the Mochat model, which is part of a swarm intelligence optimization method that mimics biological habits, is shown in Fig. 4.

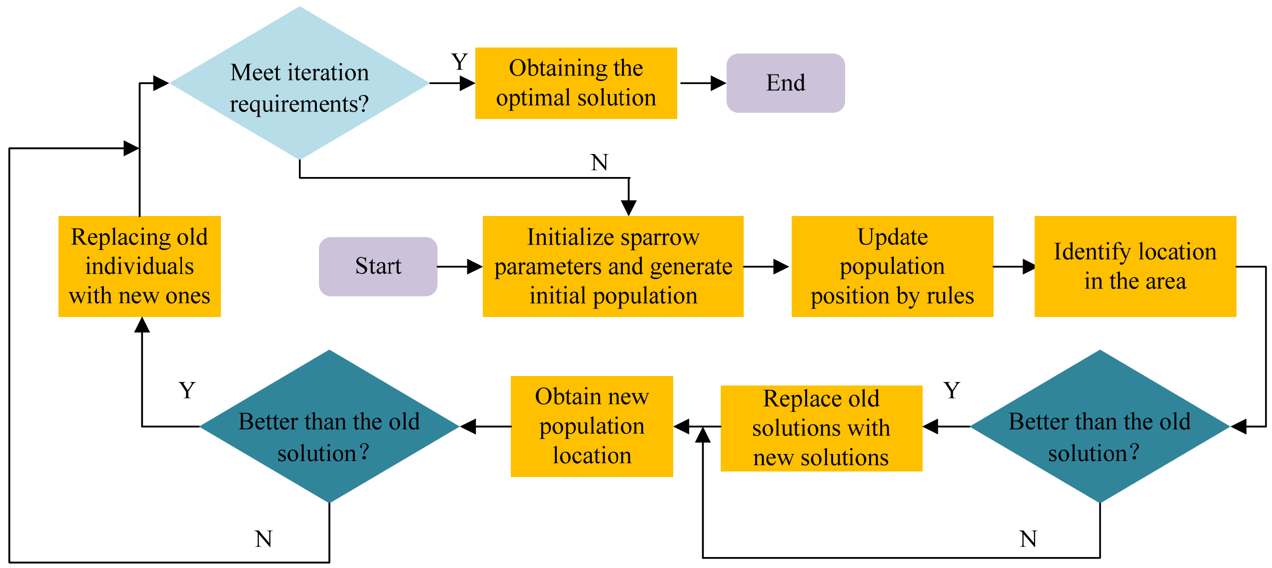


Fig. 4. Schematic diagram of sparrow model optimization principle

The sparrow model uses a division of labor between the sparrow population to find the best foraging spots, with the high-energy individuals in the population acting as food-seeking sparrows, responsible for food collection, and the remaining individuals acting as following sparrows, obtaining food by following. At the same time, between 10% and 20% of the population will act as alarm sparrows, alerting them to risks on the periphery. The individual roles of the three types of sparrows can be dynamically switched in the food search, thus improving the effectiveness of the search for things (Zhang et al., 2021). Search sparrow actions are expressed as seen in Eq. (15).

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \exp(-\dfrac{i}{aiter_{\max}}), R_2 < ST \\ X_{i,j}^{t} + QL, R_2 \geq ST, R_2 \geq ST \end{cases} \tag{15}$$

In Eq. (15), $X_{i,j}^{t}$ denotes the population individual i j in --dimensional position, $aiter$ represents the number of iterations, t denotes the number of iterations, $iter_{\max}$ denotes the maximum number of iterations, ST denotes the safety value taking values in $[0,1]$, R_2 denotes the alert value taking values in the range $[0.5,1]$, L denotes the element matrix, and Q denotes the number of normal distributions. The following sparrow actions are expressed as seen in Eq. (16).

$$X_{i,j}^{\prime t+1} = \begin{cases} Q\exp(\dfrac{X_{worst} - X_{i,j}^{t}}{i^2}), i > \dfrac{n}{2} \\ X_{p}^{t+1} + \left| X_{i,j}^{t+1} - X_{p}^{t+1} \right| A^{+} L, i \leq \dfrac{n}{2} \end{cases} \tag{16}$$

In Eq. (16), X_{worst} denotes the worst position for foraging by the following population, n denotes the population size, X_P denotes the best position for foraging by the following population, A^{+} denotes $A^T(AA^T)^{-1}$, and A denotes the element ± 1 random assignment matrix. The alarm sparrow action is expressed as seen in Eq. (17).

$$X_{i,j}^{\prime\prime t+1} = \begin{cases} X_{best}^{t} + \beta \left| X_{i,j}^{t} - X_{best}^{t} \right|, f_i > f_g \\ X_{i,j}^{t} + K\left[\dfrac{X_{i,j}^{t} - X_{worst}^{t}}{(f_i - f_w) + \varepsilon} \right], f_i = f_g \end{cases} \tag{17}$$

In Eq. (17), X_{best} stands for the alarm population foraging optimal location, β for a random number obeying normal distribution, f_g for the optimal location at this time's moderate value, f_i for the individual's moderate value, K for the directional control coefficient, taking values in the range of $[-1,1]$, and f_w for the population foraging's worst moderate value. Fig. 5 illustrates the SSA-BP engineering risk prediction model process premise.

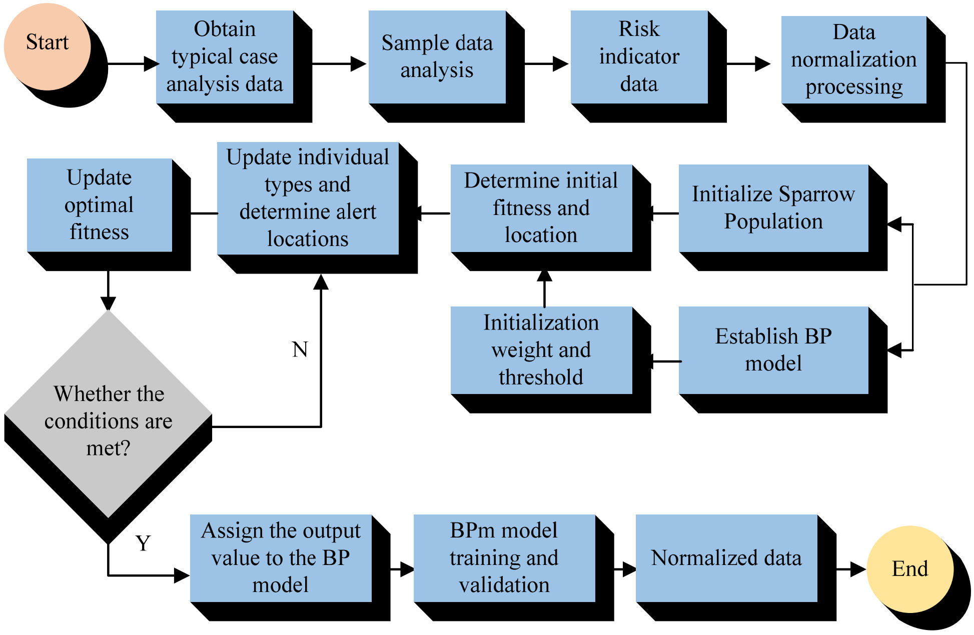


Fig. 5. Flow chart of SSA-BP engineering risk prediction model

Fig. 5 shows the training process of the SSA-BP risk prediction model. The first step is to search for case analysis data, analyze and process the data, filter out risk indicator data, and plan and process the data. Before applying the scoring results of risk factors and construction expectations as sample data for the SSA-BP engineering risk prediction model, the risk management index weights and results of home building projects must first be weighted and calculated. To prevent the model training from sliding into local convergence, the sample data is split into a test set and a training set. All data is then normalized. The PB model and the SSA model are initialized to determine the initial size of the population and the number of workers and to set the number of model training iterations. Determine the maximum number of iterations of the population and the alert value of the SSA model according to the structural characteristics of the BP model. Initialize the parameters of the BP model, get the fitness value and optimal position of the population by training the initial parameters of the BP model, and continuously update the population to get the optimal position of the population. The optimal position parameters are assigned to the BP model to complete the training of the SSA-BP risk prediction model network and obtain the risk management evaluation results of the whole process of the construction project.

4. Experimental Analysis of Engineering Project Risk Management

4.1.SSA-BP Risk Forecasting Model Performance Test

The experimental analysis process will conduct performance tests on the proposed SSA-BP model. The experimental data are taken from typical case data of engineering construction in the past ten years. Through screening, 126 sets of effective experimental data were obtained, the standardized processing was used as the model training dataset, and the model performance training was finished in MATLAB software. The experimental training parameters for the SSA-BP risk prediction model are displayed in Table 2.

Table 2. Risk prediction model experimental training parameter information

Model parameter types	Parameter value
SSA model population size	100
Iterations	720
Learning rate	0.01
Security threshold of the SSA model	0.8
BP Model Structure	14-5-1
Crossover probability	0.1
Scale factor	0.5

The traditional BP model, Particle Swarm Optimization-back propagation (PSO), was selected for experimental comparison in the study. The training loss results of the three risk prediction models are shown in Fig. 6.

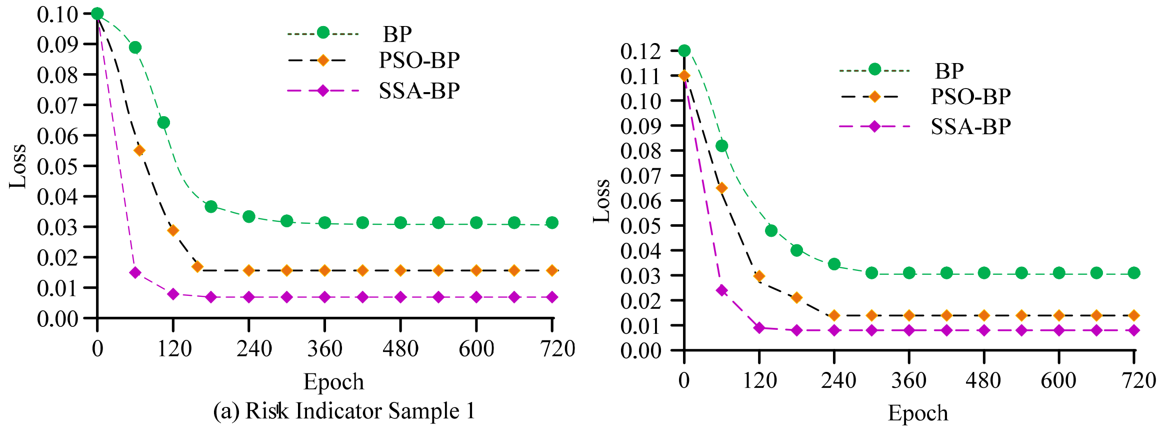


Fig. 6. Training loss results of three models

The training loss results for the three models in Risk Sample 1 are displayed in Fig. 6(a). The loss training loss values of all three risk prediction models continue to decline as the number of model training iterations rises, as seen by the changes in the curve. The training loss values for the three models in risk sample 2 are displayed in Fig. 6(b). The SSA-BP model, which converges the quickest and has the lowest loss value, has the best overall performance. The PSO-BP risk prediction model similarly demonstrated good training performance, converging after 240 iterations with a loss value of 0.016. The SSA-BP model converged after 120 iterations with a loss value of 0.0896. The vast amount of engineering project data and high correlation, which made the conventional BP model susceptible to local convergence during training, were to blame for the BP risk prediction model's poor overall performance. After 298 iterations and a loss value of 0.038, the BP model converged. As can be shown, the SSA-BP model outperforms the BP and PSO-BP models in terms of convergence and training performance. The training accuracy of the three models is displayed in Fig. 7.

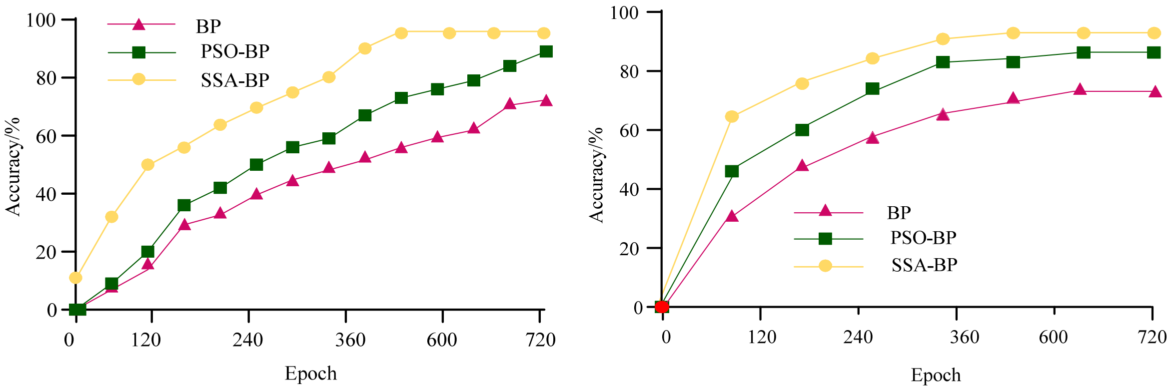
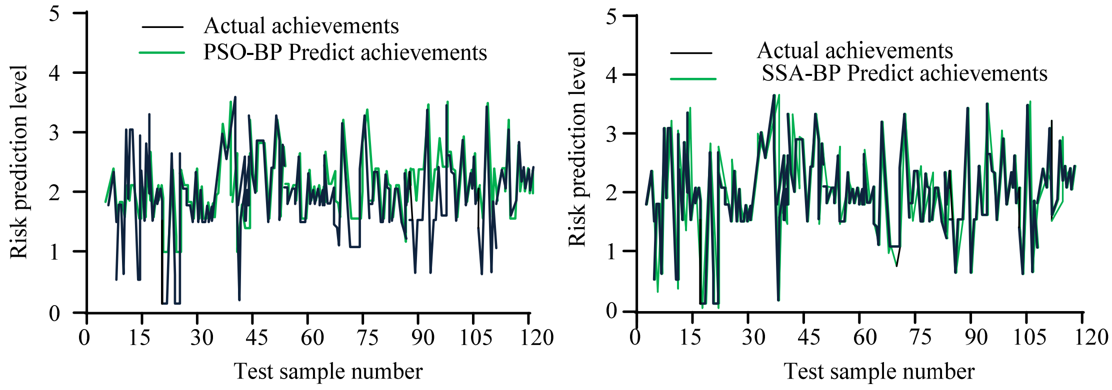


Fig. 7. Training accuracy of three models

The training accuracy results for the three risk prediction models are displayed in Fig. 7. The training results for risk sample 1 are shown in Fig.7(a), while the training results for risk sample 2 are shown in Fig. 7(a). The SSA-BP risk prediction model, which tends to converge after 698 iterations with a model accuracy of 95.68%, and the PSO-BP model, which comes in second place with a model accuracy of 92.65% at 720 iterations, have the best training accuracy of the samples, according to the data results in Fig. 7(a). After 720 iterations, the BP model performed the worst with an accuracy of 72.65. The SSA-BP model had the best training performance in Fig. 7(b), followed by the PSO-BP model, and the BP model had the poorest. The three final prediction accuracy was 92.65%, 87.65%, and 72.65%, respectively. The SSA-BP model exhibited the best training accuracy and the fastest convergence in the data training, according to the data results. To effectively manage the construction risk associated with engineering projects, SSA-BPl is used to train the engineering project risk data.

4.2. Experimental Analysis of Risk throughout the Engineering Project

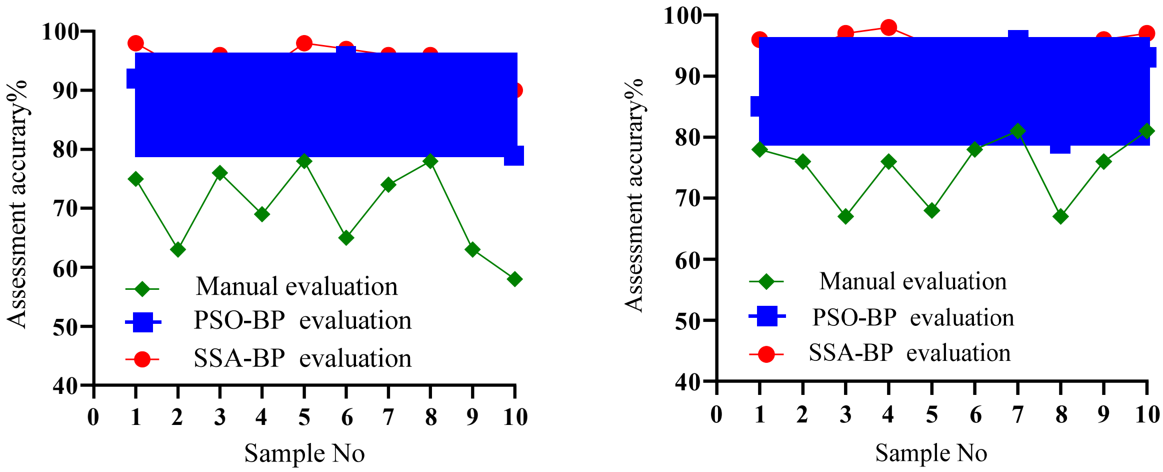
The project, which is a housing construction project with a total project investment of RMB 5.645 billion, a total project area of 1.98 million square meters, a planned land area of 86,000 square meters, and a project capacity of 42,000 people, was chosen as the subject of the experimental analysis. The findings of the project risk level prediction using the SSA-BP model, as provided by the Institute, are given in Fig. 8.



(a)Risk prediction level of PSO-BP model (b) Risk prediction level of SSA-BP model

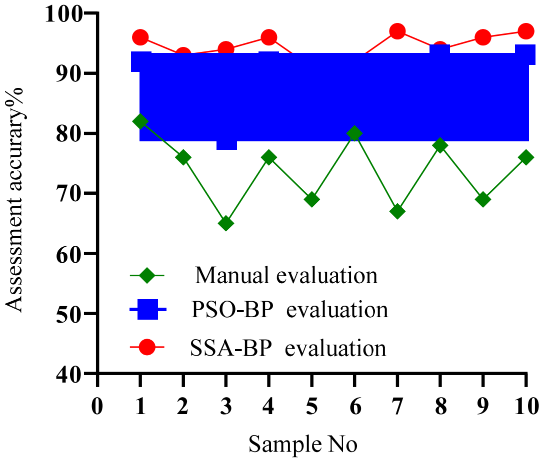
Fig. 8. Prediction results of risk levels for engineering projects

The findings of the PSO-BP model and the SSA-BP model for risk factors, respectively, are shown in Fig.8(a) and Fig. 8(b). In the figure, the solid green line displays the training prediction results of the present training model, whereas the solid black line displays the outcomes of the real risk factor ranking. According to the test findings, the SSA-BP model has a mean prediction accuracy of 92.65% compared to the PSO-BP model's mean forecast accuracy of 73.65% for samples 15 to 30. In the 120 sets of sample risk level predictions, the PSO-BP model's average forecast accuracy was 86.65% and the SSA-BP model's average prediction accuracy was 93.25%. The data results show that the suggested SSA-BP model can more effectively manage project risks and assess the degrees of project risk factors. Fig. 9 displays the risk factor forecast accuracy for engineering projects.

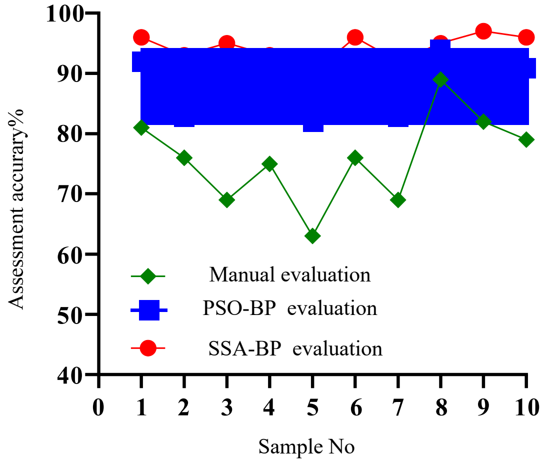


(a) Human risk (b) Manage risk

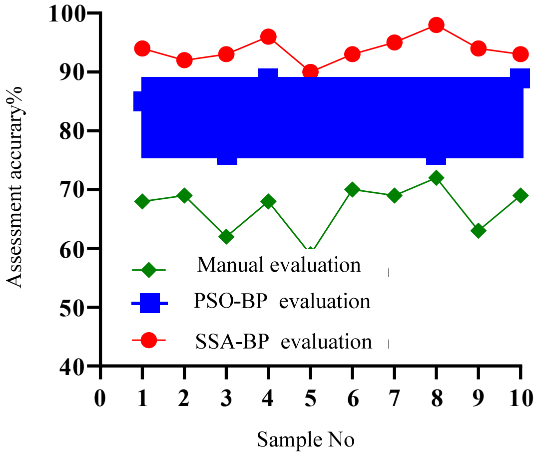
Fig. 9. Prediction results of engineering project risk factors



(c) Equipment risk



(d) Environmental risk



(e) Environmental risk

Fig. 9. Prediction results of engineering project risk factors (continued)

The training outcomes for human risk factors, management risk factors, equipment risk factors, environmental risk factors, and technical risk factors are displayed in Fig. 9(a) through Fig. 9(e), respectively. In Fig. 9(a), the SSA-BP model achieved the highest risk prediction accuracy, with prediction accuracy above 91.23% for all ten risk samples. The PSO-BP model came in second place, with an average accuracy of 87.65%, and the manual assessment came in last, with an average accuracy of 72.65%. The SSA-BP model, which has a prediction accuracy above 98.68% and an average prediction accuracy of 93.79% in samples 3 and 4, is the best risk prediction in Fig. 9(b). On average, throughout the samples of data, the PSO-BP model and manual assessment achieved a prediction accuracy of 87.65% versus 72.45%. The manual assessment fared the lowest, with an average prediction accuracy of 74.68%, while the SSA-BP model did the best in terms of forecasting equipment risk, environmental risk, and technical risk. Technical delivery and technical building technology pose the majority of technical risks in technical risk prediction, both of which are more uncertain and are influenced by environmental and human management elements. This assesses the overall performance of the model. The SSA-BP model, PSO-BP model, and manual evaluation have an average forecast accuracy of 91.68%, 82.69%, and 64.58%, respectively, in terms of technical risk. According to the experimental data, the SSA-BP model managed all five primary risk variables well, increasing risk management effectiveness by 45.86% compared to manual assessment tools and boosting risk management efficiency by 11.65% compared to the PSO-BP model. Table 3 shows the forecast inaccuracy of risk factors for engineering projects.

With 15 sets of sample data for the five primary risk factors chosen for training, Table 3 displays the results of the training of the two risk prediction model errors. In the training of human risk prediction, the SSA-BP model has a lower total training error than the PSO-BP model. In samples 3, 4, and 5, the PSO-BP model's training errors were 0.186, 0.186, and 0.256, respectively, whereas the SSA-BP model's training errors were 0.126, 0.133, and 0.140. A 26.89% improvement in error compared to the PSO-BP model in the training of five risk variables gives the SSA-BP model the best training error performance in the training of equipment risk, environmental risk, and technological risk. In terms of training error performance, the SSA-BP model outperforms the PSO-BP model by 26.89% for the five risk factors. This demonstrates that the SSA-BP model fits the requirements of whole process risk management in construction projects and performs excellently when applied to those projects.

Table 3. Prediction error results of risk indicators

Sample No	Human risk		Manage risk		Equipment risk		Environmental risks		Technical risks	
	PSO-BP	SSA-BP	PSO-BP	SSA-BP	PSO-BP	SSA-BP	PSO-BP	SSA-BP	PSO-BP	SSA-BP
1	0.156	0.128	0.265	0.123	0.264	0.126	0.235	0.123	0.256	0.138
2	0.181	0.087	0.196	0.103	0.254	0.163	0.245	0.096	0.195	0.097
3	0.186	0.126	0.198	0.146	0.196	0.156	0.196	0.125	0.186	0.134
4	0.186	0.133	0.256	0.096	0.156	0.132	0.198	0.142	0.186	0.121
5	0.256	0.140	0.186	0.076	0.135	0.096	0.256	0.096	0.195	0.131
6	0.156	0.096	0.156	0.094	0.265	0.156	0.156	0.121	0.216	0.129
7	0.189	0.120	0.176	0.156	0.196	0.134	0.189	0.096	0.264	0.114
8	0.158	0.124	0.293	0.143	0.156	0.125	0.176	0.125	0.254	0.129
9	0.176	0.103	0.194	0.146	0.245	0.096	0.293	0.125	0.196	0.109
10	0.256	0.125	0.289	0.105	0.186	0.124	0.123	0.236	0.156	0.129
11	0.195	0.096	0.297	0.126	0.215	0.153	0.103	0.091	0.153	0.107
12	0.216	0.134	0.185	0.166	0.234	0.165	0.146	0.091	0.165	0.112
13	0.189	0.142	0.165	0.099	0.196	0.096	0.158	0.123	0.186	0.123
14	0.203	0.163	0.213	0.125	0.256	0.156	0.176	0.124	0.256	0.156
15	0.216	0.126	0.189	0.026	0.275	0.123	0.189	0.103	0.156	0.124

5. Discussion

Construction risk management in construction projects is a crucial aspect of project management. It significantly affects the successful execution and smooth operation of the project. Nevertheless, present-day construction risk management is faced with several issues and challenges. Traditional risk assessment techniques are inadequate in accurately evaluating complex project scopes. The construction sector's healthy growth relies on risk management methods and tools that merge technology and experience. This research paper introduces an SSA-BP model to tackle these concerns and performs comparative experimental analysis. Experimental results reveal that the SSA-BP model provides superior performance in risk sample training loss and accuracy. Compared to traditional BP and PSO-BP models, the SSA-BP model yields better accuracy and faster convergence speed. In comparison, traditional BP models exhibit inferior loss values and accuracy, which increases the risk of local convergence. These results indicate that the SSA-BP model exhibits better convergence and training performance than traditional BP models and PSO-BP models. Secondly, for the entire process risk management experiment of specific engineering projects, the SSA-BP model is used to predict the risk level and risk factors. The SSA-BP model has a higher prediction accuracy for risk levels than the PSO-BP model, which can more accurately determine the level of project risk factors and achieve effective management of project risks. Compared with traditional manual evaluation, the SSA-BP model has significantly improved its prediction accuracy and can better solve risk management problems. Finally, it is evident from Table 3 that the SSA-BP model exhibits lower training errors in comparison to the PSO-BP model among the training errors of different risk factors. This once again proves the excellent performance of the SSA-BP model in managing process risks throughout the entire construction project. In summary, the SSA-BP model has obvious advantages in construction project risk management. The experimental comparison and analysis reveal that the SSA-BP model performs well in training loss, training accuracy, risk level prediction, and risk factor prediction. The SSA-BP model shows significant improvements in convergence, training performance, and prediction accuracy compared to traditional BP models and PSO-BP models. Thus, the SSA-BP model can be used to effectively manage and control risks, improve the success rate, and ensure the smooth operation of engineering projects during construction risk management. Moreover, the study proposes a new method and tool to handle risk management issues with great significance to the development and improvement of the construction industry, which can be referenced to handle similar problems.

6. Conclusion

One of the crucial work components of construction projects is risk management, and effective risk management is beneficial to the project's smooth progress. The project risk management case data is mined using data mining technologies, and a project full-process risk management model is built using case analysis. The BP model is presented to build a project risk prediction model, considering the complexity and nonlinear aspects of project risk components. When dealing with complicated data, traditional BP models encounter initial parameter issues, so the SSA algorithm was utilized to optimize the BP model and create the SSA-BP model project risk prediction model. The SSA-BP model achieved the best training performance in the training loss test of the three models, with the model convergent after 120 iterations and a loss value of 0.009. Sample 1 served as the experimental sample. The PSO-BP model, the second-best performer, converged after 132 iterations and currently has a loss value of 0.019. The average prediction accuracy of the SSA-BP model was 93.25%, while the average prediction accuracy of the PSO-BP model was 86.65% in the results of the project risk level prediction. The SSA-BP model, which has a 26.89% improvement in error performance compared to the PSO-BP model, has the best error performance among the two-risk prediction model error training in the five risk factors training. The SSA-BP model has excellent performance in project risk management. The main project risk content is obtained through case analysis, and the advanced PSO-BP model is used to manage and evaluate project risks, which is superior to relevant evaluation models. The technology studied has important reference value for effective construction and risk assessment in the construction industry. However, there are also shortcomings in the research. In project construction, it is necessary to consider indirect factors that cause risks and to add more risk assessment factors in the later stage. By considering more risk factors, the application effect of the technology can be improved.

Author Contributions

To create a model for project engineering's entire process risk management, information is gathered about project risk through case studies and used big data technology to screen the key risk factors. The Sparrow Search Algorithm (SSA) is introduced to optimize the construction of the SSA-BP engineering risk prediction model to achieve the management of engineering project risks. Jun Yang conducted experiments, recorded data, and analyzed the results. Sijia Yin prepared the manuscript. All authors agreed to the published version of the manuscript.

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