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Retraction

Retracted: Building Construction Design Based on Particle Swarm Optimization 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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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.

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[1] W. Song, "Building Construction Design Based on Particle Swarm Optimization Algorithm," *Journal of Control Science and Engineering*, vol. 2022, Article ID 7139230, 8 pages, 2022.

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Research Article

Building Construction Design Based on Particle Swarm Optimization Algorithm

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In order to take a scientific risk control strategy to reduce the safety risk of construction projects, a construction safety risk decision-making method based on particle swarm optimization algorithm was proposed. Through the analysis of prefabricated building construction safety risk factors, the combination of the Markov Chain and Bayesian networks method was used to estimate the probability of risk factors. The relationship between the various risk factors was described by conditional probability, and a safety risk loss-control investment double objective optimization model was built. The corresponding algorithm was designed and the R language programming was used to solve the problem. The experimental results showed that by taking a high degree of control over the risk factors of the investment strategy, when the constraint cost was RMB 200,000, the global optimal risk loss and the global optimal control cost were RMB 1,400,500 and 19,600, respectively. When the constraint cost was 280,000 yuan, the global optimal risk loss and global optimal control cost were 1.046 million yuan and 278.5 million yuan, respectively. When the constraint cost was 320,000 yuan, the global optimal risk loss and global optimal control cost were 910,100 yuan and 317,300, yuan respectively. It was concluded that, considering the risk correlation optimization model, a reasonable allocation strategy was adopted, combined with the actual situation, which performed a promoting function in improving the assembly building construction safety risk decision-making.

1. Introduction

China's annual new building area is about 2 billion square meters, accounting for 50% of the world's annual new area [1]. The construction industry has made a great contribution to the national economy by bringing GDP growth and stimulating employment. However, the traditional construction production mode has not been suitable for the rapid development of the construction industry. And there are disadvantages such as heavy workload, long night construction time, serious waste of materials and resources, too many workers, and difficult management [2]. Therefore, it is easy to cause engineering accidents. Statistics show that at least three people die in construction accidents every day in our country. However, in the UK, where the prefabrication rate is as high as 70%, at least one construction worker dies every week on average [3]. Not only that, the environmental pollution, the exhaustion of energy, and the serious haze are also worth our concern.

In the face of such a severe situation, it is imperative to vigorously develop prefabricated buildings. It can provide people with residential products with high quality, energy saving property, and environmental protection, as well as human and natural harmonious coexistence. Prefabricated components of prefabricated buildings are completed in the component factory, which can control the quality and avoid the impact of external factors on the quality of components. Prefabricated components can reduce on-site construction work and effectively inhibit dust pollution, noise pollution, and other environmental problems. Prefabricated components are standard components, which can effectively control the amount of raw materials, reduce the loss caused by on-site construction and pouring, and save resources [4]. The production environment of the factory is relatively stable, and the safety factor is much higher than that of the on-site construction. Mechanized production not only reduces the labor force greatly but also improves the work efficiency and reduces the safety risks, thus reducing the risks brought by the construction operation. See Figure 1.

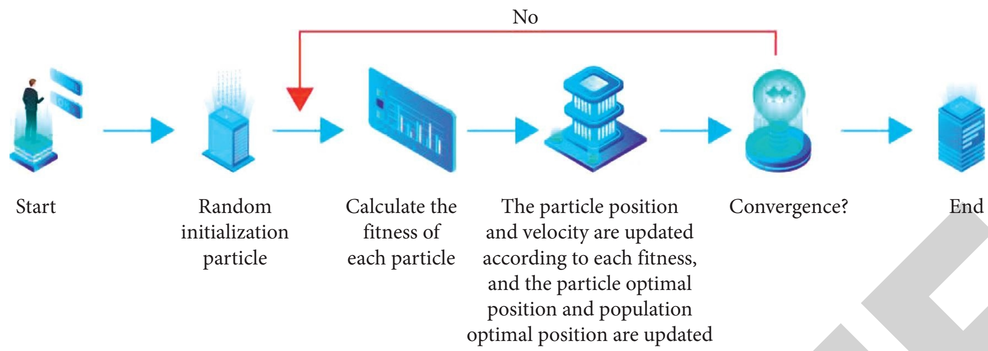


Figure 1: Based on particle swarm optimization algorithm.

2. Literature Review

From the fuzzy qualitative concept in the risk evaluation of prefabricated building safety performance, Fang analyzed the key factors affecting prefabricated structure safety. The evaluation index system was constructed. Based on the analytic hierarchy process and the entropy weight method, a cloud model-based prefabricated construction safety performance evaluation method was proposed [5]. Sukamani proposed a supply chain cost model using time-driven activity-based costing to minimize the cost of multiskill resources in prefabricated buildings [6]. The cost and time required for cross-training multiskill resources of prefabricated buildings were included in resource planning calculations by Hire, and integer and probabilistic optimization models were used to minimize the cost of using multiskill resources in off-site construction [7]. In order to optimize the cost management of prefabricated buildings and reduce the cost of capital, Tayeh discussed the variables affecting the high capital cost of prefabricated buildings and developed FAEM for cost optimization [8]. Combining the characteristics of construction engineering with order strategy, Duan built an inventory management model of building materials and realized the optimal value of inventory cost of building materials by solving a genetic algorithm [9]. Based on the meta-network analysis, Wang proposed an effective way to express the complex interaction of various factors involved in a project and extended the analysis scope to multiple dimensions to form a comprehensive project network covering the relationship between various influencing factors [10].

The above research results enrich the construction safety optimization and risk correlation theory of construction projects, but there are few relevant research on the introduction of risk correlation into the construction safety optimization of prefabricated buildings, especially for the construction safety risk expected loss and risk control investment optimization problems that need to be further investigated. In conclusion, based on the identification of safety risk factors of prefabricated building construction, the research draws the Bayesian network diagram of safety risk factors of prefabricated building construction, describes the correlation between risk factors with conditional probability, and gives the occurrence probability of risk factors with Monte Carlo simulation. On the basis of this research, the dual-objective optimization model is constructed with the minimum security risk loss of the system and the optimal risk control investment as the objective function. Multi-objective particle swarm optimization is properly improved to be applied to decision-making scheme optimization. Using the R language programming, a multiobjective particle swarm optimization algorithm is designed to solve the model, and reasonable risk control strategies are provided.

3. Research Methods

3.1. Problem Description and Relevant Theoretical Preparation

3.1.1. Problem Description. In the process of construction, the economic loss due to risk events or casualties can be obtained through statistical data intuitively. However, there are numerous risk factors involved in the process of fabricated construction. Risk factors influence and correlate with each other. So a scientific and reasonable evaluation method needs to be used to evaluate the possibility of risk factors. Traditional risk evaluation methods are mostly based on the subjective experience of experts to evaluate the probability of risk occurrence, such as the AHP method, the fuzzy logic method, etc. [11]. These methods are subjective and do not take into account the actual implementation effect of the construction site, so the evaluation results are often biased. The Bayesian network can well construct the causal dependence relationship between various variables and carry out probability analysis and simulation for each variable under different circumstances, which has a good advantage in analyzing the probability of risk occurrence. In addition, the construction safety risk factors compared with the project investment elasticity are different. Namely, the amount of risk reduction achieved is different for the same planned investment. If the risk factor is in a state of high elasticity, the corresponding control measures will have obvious effects. However, if the elasticity is low, even if the planned investment is large, it cannot guarantee that the risk level can be significantly controlled. Therefore, in the case of limited planned control resources, risk control should be invested in the link with greater flexibility, so that the total risk can be significantly reduced.

For the optimization problem of construction safety risk loss V and risk control investment C, the abstract form of the risk decision planning model is defined as (1)–(5) [12]:

$$\min V = f(x_1, x_2, \ldots, x_n), \tag{1}$$

$$s.t. C \leq C_{\max}, \tag{2}$$

$$\min C = g(x_1, x_2, \ldots, x_n), \tag{3}$$

$$V \leq V_{\max}, \tag{4}$$

$$x_i \in D, \quad i = 1, \ldots, n. \tag{5}$$

In the formulas, x_i represents the decision variable of the i th risk source R_i. $C_{\max}$ represents the upper limit of risk control investment. D represents the localized space of decision variable x_i.

3.1.2. *Theoretical Preparation*

(1) Bayesian Networks

(1) The Bayes' rule

Prior probability and posterior probability are relative to certain evidence [13]. X and Y are set as two random variables, $\{X = x\}$ as a certain hypothesis, and $\{Y = y\}$ as a group of evidence. Before considering the evidence, the probability $P(X = x)$ of the event $\{X = x\}$ is called the prior probability, and after considering evidence $\{Y = y\}$, $P(X = x \mid Y = y)$ is called the a posteriori probability. The relationship between prior probability and posterior probability expressed by the Bayes' rule is shown in Equation (6) [14].

$$P(X = x/Y = y) = \frac{P(X = x, Y = y)}{P(Y = y)}. \tag{6}$$

(2) The Bayesian networks

Bayesian Networks (BNs) are topological structures composed of a directed acyclic graph and related probability distribution functions, representing the joint probability distribution of n random variables [15], which is composed of two parts, $BNs = (G, \theta)$. G stands for a directed acyclic graph, whose nodes are random variables $X_1, X_2, \ldots, X_n$. The directed edge is the qualitative representation of the joint probability distribution, which is used to indicate the conditional independent relationship between random variables. θ represents a set of parameters used to quantify the network.

Bayesian network is used to describe the initial risk state relationship among risk sources. Assume that R_1 and R_2 are two risk sources in a construction project, and the initial risk state of R_1 will affect the initial risk state of R_2. Figure 2 shows the relationship between the initial risk state of R_1 and R_2, that is, the

Figure 2: Bayesian example diagram.

initial state of R_2 is affected by R_1. The state space of risk grade I is set as low, medium, and high. Table 1 shows the conditional probability distribution column of initial risk state of risk source R2 [16].

(2) The Markov Chain. Russian mathematician Andre Markov proposed Markov properties in 1906 [17]. Markov chains are random processes with Markov properties and state space in probability theory and mathematical statistics, which can be defined by the transfer matrix and transfer graph. The risk set of assembly building construction project is set as $R = \{R_i, i = 1, 2, \ldots, n\}$. The risk level of R_i in different risk states will only remain unchanged or transfer to a higher level without any strategy. The risk level of the state space of risk factors is set for $I = \{I_1, I_2, \ldots, I_m\}$. In the transfer process, any level forms a random sequence $I_{R_i}(t), \quad t = 0, 1, 2, \ldots; I_{R_i}(t) \in I$. Assume that the future risk level of the risk source is only related to the current risk level, that is, there is no aftereffect of the grade state, so the transfer of the risk source level constitutes a Markov chain, which satisfies the following equation (7) [18]:

$$\begin{aligned} &P\left[I_{R_i}(t+1) \mid I_{R_i}(0), I_{R_i}(1), \ldots, I_{R_i}(t)\right] \\ &\quad = P\left[I_{R_i}(t+1) \mid I_{R_i}(t)\right]. \end{aligned} \tag{7}$$

Further, it is assumed that the transfer between risk levels is a time-homogeneous Markov chain, and the one-step transfer probability of R_i transferring from risk level I_j to risk level I_k is expressed in formula (8) below:

$$p_i(j,k) = P\left[I_{R_i}(t+1) = I_k \mid I_{R_i}(t) = I_j\right], \quad t = 0, 1, 2, \ldots \tag{8}$$

In the state space I, the one-step transition probability matrix constituted can be expressed as formula (9):

$$\begin{pmatrix} p_i(1,1) & p_i(1,2) & \cdots & p_i(1,m) \\ p_i(2,1) & p_i(2,2) & \cdots & p_i(2,m) \\ \vdots & \vdots & \ddots & \vdots \\ p_i(m,1) & p_i(m,2) & \cdots & p_i(m,m) \end{pmatrix}. \tag{9}$$

In the formula, $\sum_{k=1}^{m} p_i(j,k) = 1, \quad j = 1, 2, \ldots, m$.

(3) Joint Distribution of Accidents. Suppose that the expectation of joint accident distribution of risk source $R_1, R_2, \ldots, R_n$ is $\mu = (\mu_1, \mu_2, \ldots, \mu_n)^T$, that is, the accident rate of risk source R_i is μ_i. Then μ_i describes the average level of accident probability after R_i moves from initial risk state $I_{R_i}(0)$ to state $I_{R_i}(1)$ [19].

Table 1: Joint probability distribution column of risk sources R1 and R2.

	$R_2 =$ Low	$R_2 =$ Medium	$R_2 =$ High	Notes
$R_1 =$ Low	P_{11}	P_{12}	P_{13}	$P_{11} + P_{12} + P_{13} = 1$
$R_1 =$ Medium	P_{21}	P_{22}	P_{23}	$P_{21} + P_{22} + P_{23} = 1$
$R_1 =$ High	P_{31}	P_{32}	P_{33}	$P_{31} + P_{32} + P_{33} = 1$

3.2. Construction Safety Risk Optimization Model of Prefabricated Building Construction

3.2.1. Model Description. For risk source R_i, its decision localization space D is divided into two categories, 0 and 1, $D = \{0, 1\}$. That is, the degree of risk investment in R_i is divided into two different levels. $x_i = 0$ has a low level of investment. $x_i = 0$ represents a high level of investment. Suppose that the risk loss of R_i under the investment degree of x_i is L_{i,x_i}, and the control investment is C_{i,x_i}, then the relationship between the risk loss and the control investment under different investment degrees is as follows:

$$L_{i0} > L_{i1}, \quad i = 1, \ldots, n, \tag{10}$$

$$C_{i0} < C_{i1}, \quad i = 1, \ldots, n. \tag{11}$$

Construction safety risk loss V is depicted by the overall expected risk loss value of the system, then V in (12) is defined as

$$f(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} \mu_i L_{i,x_i}. \tag{12}$$

In formula (13), the system overall control investment $g(x)$ is defined as

$$g(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} C_{i,x_i}. \tag{13}$$

3.2.2. Algorithm Solution Design. The particle swarm optimization (PSO) algorithm is a kind of meta-heuristic algorithm based on swarm, which has the advantages of simple setting, fewer optimization parameters, and fast convergence. A large number of practical problems can be transformed into multiobjective optimization problems. The particle swarm optimization algorithm has been widely used to solve multiobjective optimization problems in recent years due to its excellent characteristics in intelligent optimization algorithms. Multiobjective optimization problems cannot compare a set of advantages and disadvantages of noninferiority solution sets, while the actual decision-making situations usually need to select one from noninferiority solutions or some solution as a final solution problem. The main task of solving the multiobjective optimization problem is to find the noninferiority solution set as much as possible or get the best noninferiority solution set. In the research, in order to minimize the goal V and C, a particle is set as S_0. For any particle $x_i, x_j \in S_0$. Then the objective function value is $V^{(i)}$, $C^{(i)}$ and $V^{(j)}$, $C^{(j)}$, respectively. If $V^{(i)} \leq V^{(j)}$ and $C^{(i)} \leq C^{(j)}$, then x_i is superior to x_j. If $V^{(j)} \leq V^{(i)}$ and $C^{(j)} \leq C^{(i)}$, x_j is superior than x_i . In other cases, x_i and x_j are called noninferiority relations. x_0 is called a noninferiority particle if $\exists x_0 \in S_0$, for $\forall x_i \in S_0$, there is a noninferiority relationship between x_0 and x_i or x_0 is superior than x_i.

The established optimization model is a 0–1 integer programming model, so it is improved on the basis of the multiobjective particle swarm optimization algorithm. And the value range of particles in each position dimension is limited to {0, 1}. The inertia weight W is converted by the linear decreasing weight (LDW) strategy formula proposed by Shi, and the particle velocity update formula S is converted by the form constraint transformation function sigmoid (v). t is the iteration cycle, k is the particle number, and i is the risk source number. Let $x_k^{(t)} = [x_{k1}^{(t)}, x_{k2}^{(t)}, \ldots, x_{kn}^{(t)}]\prime$ be the position vector of particle k in round t iteration, $v_k^{(t)} = [v_{k1}^{(t)}, v_{k2}^{(t)}, \ldots, v_{kn}^{(t)}]\prime$ be the position vector of particle k in round t iteration, $\xi_k^{(t)} = [\xi_{k1}^{(t)}, \xi_{k2}^{(t)}, \ldots, \xi_{kn}^{(t)}]\prime$ be the historical optimal position vector of particle k before round t iteration, and $\xi_g^{(t)} = [\xi_{g1}^{(t)}, \xi_{g2}^{(t)}, \ldots, \xi_{gn}^{(t)}]\prime$ be the global optimal position vector before round t iteration. The specific implementation steps [20,21] are as follows:

Step 1: The parameters and initialization of the particle swarm are determined. The number of particles is m, the number of iterations is T, the upper limit of the number of elements $S_{\max}$, the acceleration factors φ_1, φ_2, and the inertial weight parameters $v_{\max}$ and $v_{\min}$ are determined. Initialized particle position is $x_1^{(0)}, x_2^{(0)}, \ldots, x_n^{(0)}$. The probability of each dimension of particles are taken as 0 or 1. Initialized particle velocity is $v_1^{(0)}, v_2^{(0)}, \ldots, v_n^{(0)}$. Random number of Uniform$(-1, 1)$ distribution is taken as each dimension of each particle.

Step 2: Take $\xi_k^{(0)} = \mathbf{x}_k^{(0)} (k = 1, 2, \ldots, n)$ and determine the noninferior particle set $S = \{o_1, o_2, \ldots, o_l\}$ according to $\xi_1^{(0)}, \xi_2^{(0)}, \ldots, \xi_n^{(0)}$.

Step 3: Update $\xi_k (k = 1, 2, \ldots, n)$ and the noninferior solution set. For particle k, if $\mathbf{x}_k^{(t)}$ is superior than $\xi_k^{(t)}$, then $\xi_k^{(t+1)} = x_k^{(t)}$. If $\xi_k^{(t)}$ and $\mathbf{x}_k^{(t)}$ are noninferior relationship, then $\xi_k^{(t)}$ or $x_k^{(t)}$ are randomly chosen as $\xi_k^{(t+1)}$ with equal probability. According to $\xi_0^{(1)}, \xi_0^{(2)}, \ldots, \xi_0^{(t+1)}$, the temporary noninferior solution set $S\prime$ is determined. According to S and S' , the new noninferior particles are determined. In accordance with it, S. is updated.

Step 4: Calculate the probability information of noninferior particles in S. The particle position space is a set of 2^n points. Suppose the particles of the noninferior solution set cover h points $H_1, H_2, \ldots, H_h$ in space.

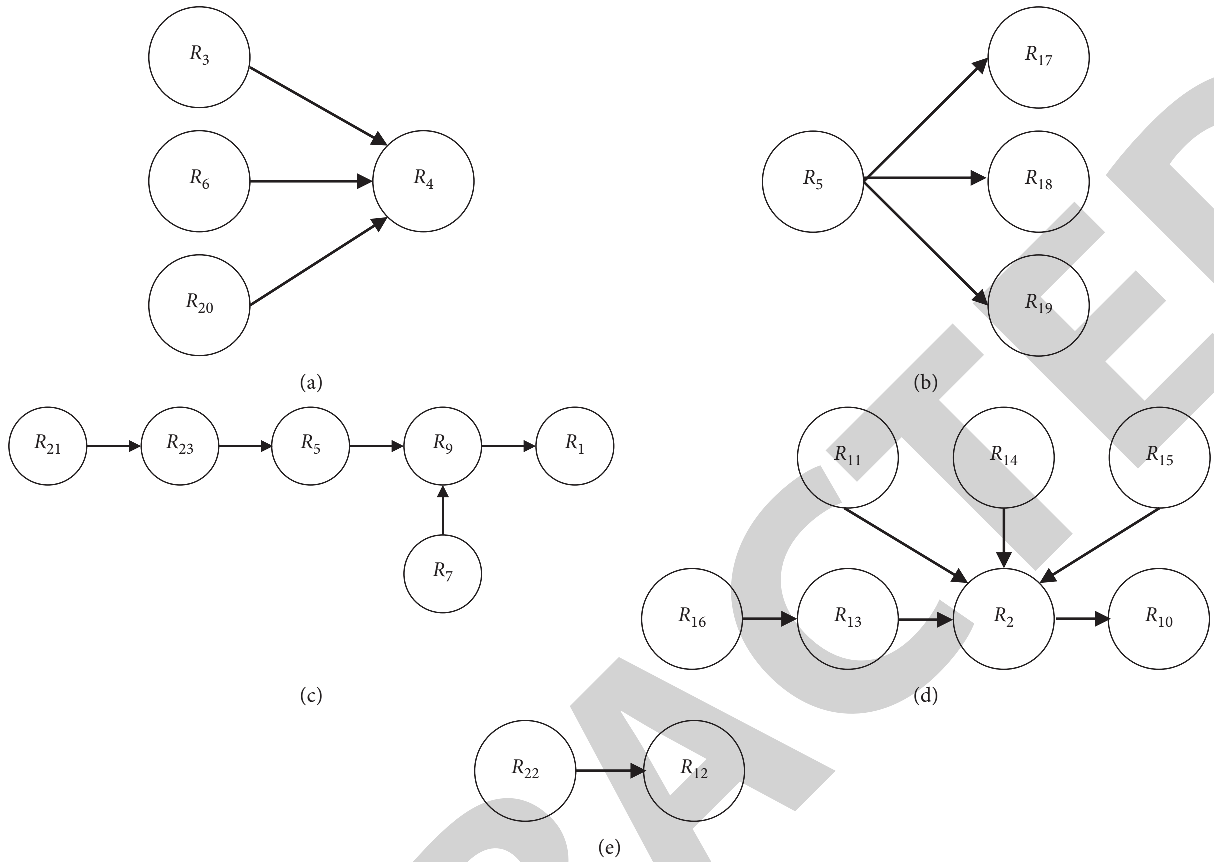


Figure 3: Diagram of Bayesian network risk factors.

Suppose the point H_b have l_b particles $\sum_{b=1}^{h} l_b = l$, then take the characteristic probability of the noninferior particle q_k as

$$q_k = \frac{1}{h_b}, o_k \in H_b, \quad k = 1, 2, \ldots, m. \tag{14}$$

If $l > S_{\max}$, $S_{\max}$ elements are randomly selected from S according to the unequal probability sampling method as the noninferior solution, and the sampling probability is the calculation result of Equation (14). According to Equation (14), the characteristic probability of noninferior particles is redefined. ξ_g is randomly selected from S by the equal probability sampling method.

Step 5: Update v and particle swarm velocity and position. As shown in Formula (15)–(18)

$$v^{(t)} = v_{\max} - \frac{v_{\max} - v_{\min}}{T} t, \tag{15}$$

$$v_k^{(t+1)} = v^{(t)} v_k^{(t)} + \varphi_1 r_{1k}^{(t)} \xi_k^{(t)} - x_k^{(t)}] + \varphi_2 r_{2k}^{(t)} \cdot \xi_g^{(t)} - x_k^{(t)}], \tag{16}$$

$$sigmoi\ d\left(v_{ki}^{(t+1)}\right) = \frac{1}{1 + \exp\left[-v_{ki}^{(t+1)}\right]}, \quad k = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n, \tag{17}$$

Table 2: State transition matrix of risk R_1.

R_1	Low	Medium	High
Low	0.38	0.32	0.28
Medium	0.00	0.55	0.46
High	0.00	0.00	1.00

$$x_{ki}^{(t+1)} = \begin{cases} 1, & r_{ki}^{(t+1)} < \text{sigmoid}\left[v_{ki}^{(t+1)}\right], \\ 0, & \text{others} \end{cases} \quad k = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n. \tag{18}$$

In the formulas, $r_{1k}^{(t)}, r_{2k}^{(t)}, \ldots, r_k^{(t)} = [r_{k1}^{(t)}, r_{k2}^{(t)}, \ldots, r_{kn}^{(t)}]'$ is an n dimensional vector, and the value of each dimension is a random number with Uniform (0,1) independence and distribution.

Step 6: If the iteration is completed, the particle position with the minimum value of $V + C$ is selected from S as the global optimal position. Otherwise, return to Step 3.

4. Results Analysis

4.1. Security Risk Factor Analysis and Bayesian Networks Structure Construction. A prefabricated building project in a city was elected as a sample for example verification. On the

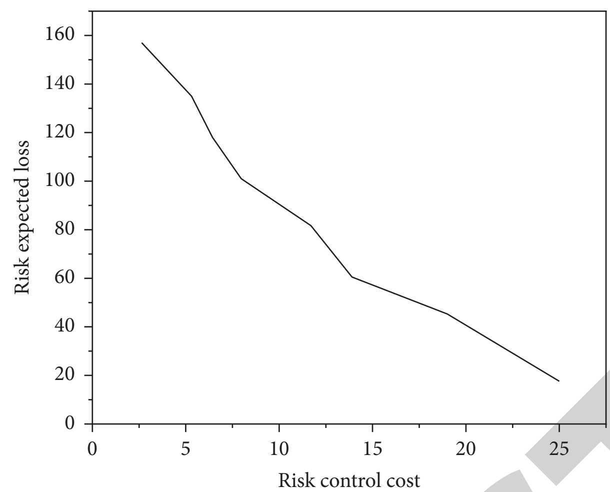
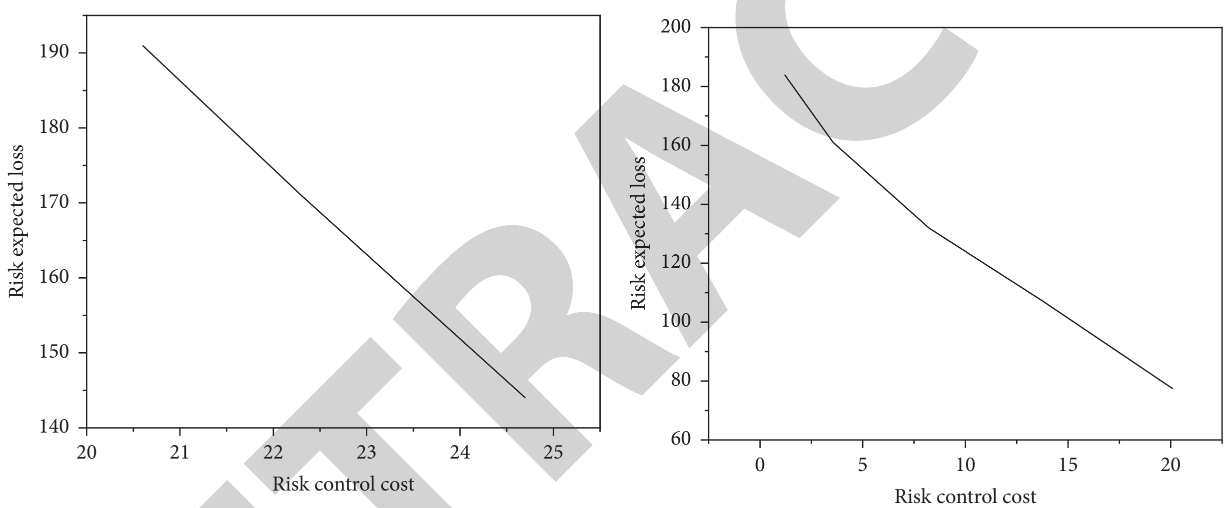


Figure 4: Diagram of V–C without constraints.



(a) (b)

Figure 5: Comparison of noninferior solution sets under different constraints. (a) The cost constraint is 200,000 yuan. (b) The cost constraint is 240,000 yuan.

basis of the existing literature review, combined with the principle of risk evaluation index selection, the project construction safety risk factors were mainly divided into 6 aspects, and these 6 aspects mainly involved 23 risk sources. Risk control cost and risk loss (the unit is ten thousand yuan) were obtained by referring to the relevant data of the project in the last three years and by asking relevant project personnel. The final results were averaged. Combined with the above risk factor analysis, the Bayesian network structure of the project was drawn [22], as shown in Figure 3.

4.2. Construction of State Risk Probability Table and Transition Matrix. Through collecting similar items for statistical analysis, the probability of occurrence of each risk factor in different states was determined.

On the basis of the probability of each risk occurring in different original states and considering the characteristics of each risk factor, multiple state transition matrices were generated. Due to space limitation, the research took the state transition matrix of risk R_1 as shown in Table 2 for example. When R_1 was in a low-risk state, there were three risk transfer states. The probability of maintaining a low-risk state is 0.38, the probability of transferring to a medium-risk state 0.33, and the probability of transferring to a high-risk state is 0.29. When R_1 was in the medium-risk state, it was the same for other situations except when it could not be transferred to the low-risk state [23]. When R_1 was in the high-risk state, it could only keep the high-risk state and could not transfer to the low- or medium-risk state without adopting the strategy. See Table 2.

4.3. Optimization Model Solution. The parameters are set as follows: $\omega_{\max} = 0.9$, $\omega_{\max} = 0.4$, $T = 5000$, $\varphi_1 = \varphi_2 = 1.496$, particle population size of 100, external memory capacity of 200.

In order to reflect the specific relationship between the expected risk loss and the risk control investment, it is assumed that the control investment and the overall risk loss value of the system are unconstrained under the condition of sufficient capital. The calculation results are shown in Figure 4, from which it can be seen that the risk loss value presents a nonlinear relationship with the risk control investment. With the increase of risk control investment, the overall risk loss value of the system gradually decreases. When the control investment approaches the minimum value, the system risk loss is the maximum. When the risk control investment approaches 400,000 yuan, all risks are controlled to the maximum extent.

However, due to limited funds, it is impossible to control all risks without limiting the actual projects, so risks should be controlled selectively according to the actual investment budget. In the research, two different constraint conditions are set. Constraint 1: the upper limit of overall risk loss $V_{\max} = 2$ million yuan, as well as the upper limit of total risk control investment $C_{\max} = 200,000$ yuan. Constraint 2: $V_{\max} = 2$ million yuan, $C_{\max} = 240,000$ yuan. Noninferior solution sets are obtained under different constraints, as shown in Figures 5(a) and 5(b), respectively. It can be seen from Figure 5 that V–C is approximately nonlinear under different constraints. Noninferior solution sets are shown in Figure 5(a) and Figure 5(b), while the noninferior points in Figure 5(a) are relatively dispersed.

The optimization control effects under different constraints are analyzed. When the constraint cost is RMB 200,000, the risk factors for adopting high degree of control investment strategy are $R_1, R_5, R_6, R_7, R_{14}, R_{19}, R_{20}, R_{22}$. Then the global optimal risk loss and the global optimal control cost are 144. 500,000 yuan and 199,600 yuan, respectively [24].

When the constraint cost is 240,000 yuan, the risk factors for adopting high degree of control investment strategy are R_1, R_2, R_5, $R_6, R_7, R_{14}, R_{15}, R_{19}, R_{20}, R_{21}$, R_{22}, R_{23}. Then the global optimal risk loss and global optimal control cost are 1,194,100 yuan and 239,400 yuan, respectively [25].

5. Conclusions

Through the analysis of prefabricated building construction safety risk factors, the combination of the Markov Chain and Bayesian networks methods was used to estimate the probability of risk factors. The relationship between the various risk factors was described by conditional probability, and a safety risk loss-control investment double objective optimization model was built. The corresponding algorithm was designed and the R language programming was used to solve the problem. In the model, different control strategies can be adopted according to the available risk control investment, which provides a new idea for assembly building construction safety risk management.

For the control intensity of each risk factor, only two degrees of comparison were considered. The control degree of each factor was set as a continuous variable, and the control degree was expressed by a function model. A variety of algorithms were used to verify the model.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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