Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 8786849, 11 pages
https://doi.org/10.1155/2022/8786849

Research Article

Risk Decision-Making of Multiobjective Chaos Search in Construction Projects considering Loss Level and Probability Level

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Received 18 January 2022; Revised 15 February 2022; Accepted 23 February 2022; Published 19 March 2022

Academic Editor: Gengxin Sun

In engineering projects, the coordination and management of multiple objectives is an important part of project management, which has a direct impact on the realization of objectives in terms of project duration, cost, and quality. The current engineering project investment presents the characteristics of large scale, long period, and many risks, which puts forward higher requirements for the multiobjective coordinated management of the project. Therefore, the analysis and optimization of the various objectives of the engineering project is the basis for achieving multiobjective balance and coordination. The comprehensive consideration of the risks faced by the engineering project and the dynamics of the environment in which it is located can make the objective optimization more realistic. On the basis of risk identification and risk evaluation, this paper is committed to considering multiple objective factors that affect the outcome of risk decision-making to achieve the optimization of decision-making schemes and applies multiobjective genetic algorithm to the optimization of decision-making schemes, thus finding a way to optimize the decision-making scheme. This paper analyzes the research progress and status of construction project risk management decision and multiobjective evolutionary algorithm and points out the imperfections of the current research. Then it introduces the related theory of construction project risk management decision, the related terminology of multiobjective optimization problem and the method used in this paper —the principle, process, and characteristics of genetic algorithm and prepares for the following problem solving. In this paper, a mathematical model for multiobjective decision-making of engineering project risk management is established, and the multiobjective genetic algorithm is used to solve the model. Through the analysis of examples, a series of Pareto optimal solutions with good convergence and diversity are obtained, the best combination of various risk control measures is found, and three goals of risk evaluation value, management cost, and risk loss are achieved. The two models with or without risk correlation present certain differences, the model with correlation considered is more accurate and applicable than the model without correlation considered in the existing research.

1. Introduction

For a construction project, risks are latent in the whole process, all aspects and even all links, so a comprehensive and systematic risk management approach is needed [1]. Therefore, in order to strengthen construction project risk management more effectively and improve the level of risk decision-making, only to achieve a single goal (such as minimizing the cost of risk control or minimizing the loss caused by risk, etc.) can no longer meet the actual needs but need to consider multiple goals at the same time to ensure effective risk control [2]. For example, when the aforementioned collapse in Dongguan construction process caused casualties, there is a certain correlation between the two risk factors of "collapse accident" and "casualties"; when the collapse was caused by bad weather changes, there is a certain correlation between the two risk factors of "collapse accident" and "casualties" [3]. There is also a correlation between "severe weather change" and "occurrence of collapse" [4]. There are many other examples of correlation between risk factors, but the current theoretical research does not have a precise definition of risk correlation, and the risk correlation is not taken into account in the research of project risk decision model, which leads to the lack of accuracy and applicability of the risk decision model [5]. Chaos is a relatively common nonlinear phenomenon because it can be experienced in a specific region without repetition of all states, so it can be used as an effective mechanism to jump out when the particles stall. Combining it with particle swarm algorithm will be very useful for improving the performance of particle swarm algorithm [6]. The main idea of chaos search is to generate a random initial chaotic variable when there is a particle in stagnation, use the chaos mapping function to get a chaotic sequence, and "scale up" the chaotic variable to the search space of the optimization problem using the carrier wave, if the particle with the best fitness function value in the chaotic sequence is better than the stagnant particle, then. If the particle with the best fitness function value in the chaotic sequence is better than the stagnant particle, then replacement is performed [7]. Multiobjective optimization is a class of optimization problems that we often encounter in real life. The concept was introduced by French economist V. Pareto as early as 1896, and its main characteristic is that the objectives may be contradictory to each other, so it is generally impossible to optimize all the objectives in the optimization problem together [8]. In the development of multiobjective optimization for more than 100 years, there have been more than 30 kinds of solutions [9]. Its optimization results are highly competitive. However, it cannot be ignored that the particle swarm algorithm, as a relatively new evolutionary algorithm that has not appeared for a long time, still suffers from the lack of sound theoretical research, has not really formed a perfect theoretical system, and its application scope has not yet been sufficiently expanded [10]. For example, the current particle swarm algorithms are basically for single-objective optimization problems, which is not in line with the fact that most of the optimization problems are multiobjective optimization problems [11]. Although some scholars have studied the application of PSO to multiobjective optimization, it is often only for low-dimensional optimization problems, but once it is applied to solve relatively complex high-dimensional multiobjective optimization problems, the drawback of premature convergence is almost unavoidable [12].

Owing to its simple concept and easy implementation, it has received a lot of attention from scholars because it was proposed, and now it is widely used in image processing, neural network, objective optimization, and other fields. In this paper, the basic principle of particle swarm algorithm, parameter setting, algorithm improvement, and its application in multiobjective optimization are studied. The particle-swarm-based algorithm is able to search for solutions in the solution space implicitly and in parallel, and it can improve the search efficiency of the algorithm by the similarity between solutions, which is very suitable for dealing with multiobjective optimization problems. In this paper, we introduce the optimal solution evaluation selection and chaos idea into the multiobjective particle swarm algorithm and propose a chaotic multiobjective particle swarm algorithm based on optimal solution evaluation selection. The concept of credibility is proposed to evaluate the results, and the obtained results are fitted into a curved surface through linear interpolation, so as to provide an intuitive basis for risk decision-making. The decision-making scheme obtained from the solution results also provides a strong scientific basis for the actual risk control.

For the problems of premature convergence of particle swarm algorithm, a particle swarm improvement algorithm based on chaos idea is proposed, which uses chaotic sequence to reinitialize the inert particles that fall into local extrema during the iteration process, thus helping the inert particles to jump out of the local extrema and search for the global optimal solution quickly.

2. Related Work

At present, the research on construction project risk management at home and abroad is mainly on the identification of risk factors and risk response strategies, for example, Song elaborates the relevant issues about risk management of engineering projects, including the definition, characteristics and corresponding response strategies of construction project risks, and analyzes the problems arising from risk management of large construction projects in China from the perspective of safety [13]. Many scholars also study how to make reasonable and effective assessment of construction project risks, consider integrating relevant risk assessment and risk influencing factors to establish risk assessment system; make risk assessment of construction project based on Bayesian network; research on risk decision objectives for construction project, research on decision objective system for cross-regional major engineering projects [14]; propose risk-value model for risk decision, by establishing function of risk and value as decision objectives, and then transform the multiobjective problem into a single-objective problem; multiobjective optimization algorithm based on decomposition to consider the multiobjective equilibrium optimization of large engineering projects with risk; multiobjective study of risk decision using genetic algorithm for construction projects, considering the relationship between risk loss, risk control cost, and risk evaluation value and conducting decision analysis [13].

In order to improve the performance of the algorithm and accelerate the convergence speed of the algorithm, the concept of inertia weights is introduced on the basis of the basic PSO algorithm, and the size of the inertia weights is chosen to be dynamically adjusted during the iteration process in order to balance the convergence speed and the global nature of the algorithm, and the iterative equation is called the standard particle swarm algorithm. In the standard PSO algorithm, the inertia weights are taken to be linearly decreasing as the iteration proceeds, which makes the algorithm have a strong global search capability at the beginning of the iteration and a strong local search capability at the late iteration [15]. An improved algorithm for dynamically adjusting the inertia weights based on fuzzy rules is proposed. The main idea of the algorithm is to use the inertia weights to formulate fuzzy inference rules and the corresponding affiliation functions, so as to determine the increment of inertia weights [16]. The test results show that the fuzzy adaptive method has better results compared with the method with linearly decreasing inertia weights. In China, in order to discuss the selection of time-varying weights and fixed weights, systematic experiments on the selection of weights, and the effects of parameter changes on the performance of the algorithm are discussed in detail in terms of the size of the population, the dependence of the problem, and the topology of the algorithm [17].

The analysis results show that the value of inertia weights should be reduced appropriately when the population size increases, and the dependence of the algorithm performance on the problem is not very obvious, while the value of inertia weights has more freedom when under the local version [18]. A method for decreasing the cosine of the inertia weights as the number of iterations increases is given, and good test results are also obtained. The scholars found that the standard PSO algorithm has the disadvantage of falling into the local optimal solution, that is, the algorithm converges prematurely during the iterative process and does not perform the global search well, and the diversity of the population decreases significantly with the increase of the number of iterations due to the fast convergence of the algorithm, which may not converge to the global optimum [19]. Based on the idea of spatial domain, an improved algorithm was proposed in which particles in the same spatial domain evolve separately and dynamically adjust the threshold to maintain the population diversity [20].

3. Multiobjective Search for Engineering Risk Decisions

3.1. Multiobjective Algorithm with Chaotic Search. Chaos is a relatively common nonlinear phenomenon that can be used as an effective mechanism to jump out of a particle stagnation because it can go through all states in a specific region without repetition. Combining it with particle swarm algorithm will be very useful for the improvement of the performance of particle swarm algorithm. The main idea of chaos search is to generate a random initial chaotic variable when a particle is stagnant, use the chaos mapping function to obtain a chaotic sequence, and "scale up" the chaotic variable to the search space of the optimization problem using a carrier wave. The replacement is carried out. The mathematical procedure is as follows:

A one-dimensional vector is randomly generated if there are particles in the stagnant state during the iteration.

$$x_0 = \{x_{01}, x_{01}, \ldots, x_{0n}\}, \quad x_{0n} \in [0,1]. \tag{1}$$

Using the random vector 0_y as the initial value of the iteration, the chaotic sequence is obtained by iterating according to the modified Tent chaos mapping equation:

$$N_M = \{x_{01}, x_{01}, \ldots, x_{0n}\},$$

$$x_{n+0} = \begin{cases} x_n + \dfrac{\text{random}[0,1]}{1000}, & 0 < y_n < 0.5, \\ 1 - x_{n-1} - \dfrac{\text{random}[0,1]}{1000}, & 0.5 < y_n < 1. \end{cases} \tag{2}$$

where $n = 0, 1, 2, 3, \ldots$.

The chaotic variable y_{nd} is enlarged into a spatial domain centered on the current particle with a radius of R_{id} according to Eq. where R_{id} denotes the chaos search radius, which is generally taken to be 20% of the defined domain of the function independent variable x:

$$R_{i\,d} = x_{i\,d} - \frac{\text{random}[0,1]}{1000}. \tag{3}$$

Calculate the fitness function value $f(y_n)$, while updating the optimal position x_i and the optimal fitness function value f at any time during the search process. If f is to be better than F_i, the original velocity and position of the stalled particle are replaced by the new velocity v and position x, where v is taken as shown in equation:

$$x_i = \frac{\left\| x_{i\,d} - \text{random}[0,1]/1000 \right\|}{x\prime}. \tag{4}$$

3.2. Particle Swarm Algorithm. In the iterative process of the particle swarm algorithm, a unified mechanism consisting of stagnation detection and stagnation processing is used to keep the population from stagnating or to jump out quickly when stagnation occurs. The stagnation detection is the stagnation determination method of the particles, while the stagnation processing is the chaotic search technique used when stagnation occurs. This section specifies the stagnation determination method for particles. Assume that F_i and $F_{p\text{best}}$ are the current fitness function value and the individual historical optimal fitness function value of the ith particle, respectively, and δ and N_c are the predetermined constant thresholds. If $\Delta F_i < \delta$ is satisfied for N_c consecutive times in the iteration, the particle is determined to be stalled, where ΔF_i is taken as shown in equation:

$$\Delta F_i = \frac{\left[F_i - F_{p\text{best}}\right]}{F_i}. \tag{5}$$

The particle swarm algorithm with chaotic search is shown in Figure 1.

Step 1. Initialization: Set the population size and the maximum number of iterations of the population and use chaos search technique to randomly initialize the position and velocity of the particles.

Step 2. Evaluate the fitness function value F_i of the particles in the population and update the individual historical optimal position and its optimal value $F_{p\text{best}}$ and the global historical optimal position and its optimal value $F_{g\text{best}}$.

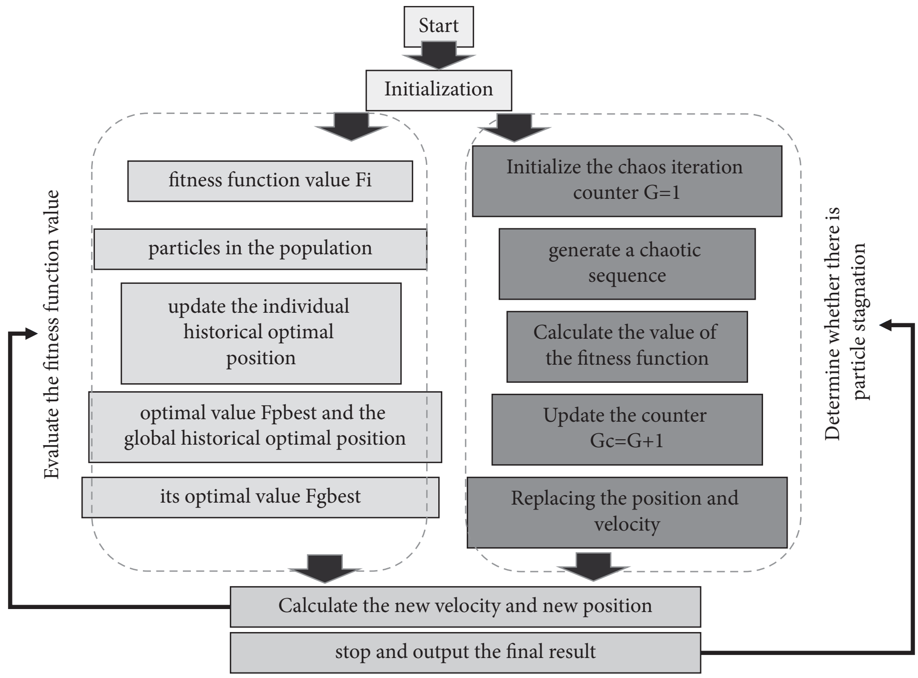

Figure 1: Particle swarm algorithm with chaotic search.

Step 3. Determine whether there is particle stagnation, if not, go to Step 4, if yes, then perform chaos search.

(1) Initialize the chaos iteration counter $G = 1$ and set the number of chaos searches $N_{\max}$ and the search radius R_{id}.

(2) Generate a chaotic sequence according to the improved Tent chaos mapping equation and scale it up to a spatial domain with a radius of R_{id} centered on the stalled particle according to equation.

(3) Calculate the value of the fitness function $f(y_n)$ of the particle and update the optimal f^* and x_i^* in the chaotic search process.

(4) Update the counter $G_c = G + 1$ and skip to Step 2 until $G_c > N_{\max}$.

(5) Replacing the position and velocity of the stalled particles with x_i^* and v_i^* during the chaotic search.

Step 4. Calculate the new velocity and new position of each particle.

Step 5. If the termination condition is met or the maximum number of iterations is reached, then stop and output the final result, otherwise, go to Step 2.

3.3. Risk Correlation Interactivity Coefficient Inscription. Interactivity coefficient, as an important indicator, is used to characterize the degree of correlation between risks and is generally taken as [−1, 1], (0,1] means that the correlation between two risks is positive, that is, if two risks occur simultaneously, the sum of their losses is greater than the sum of their losses occurring separately; 0 means that there is no correlation between two risks at the loss level, that is, the two risks do not affect each other, and their losses exhibit additivity; [−1,0] means that the correlation between two risks is negative, that is, the sum of their losses occurring simultaneously is smaller than the sum of their losses occurring separately. (−1, 0) indicates that the correlation between the two risks is negative, that is, the sum of losses generated by their simultaneous occurrence is smaller than the sum of losses generated by their separate occurrence. Assuming that two risks i and risk j are correlated, define I_{ij} as the coefficient of interactivity between risk i and risk j. Obviously $I_{ij} = I_{ji}$. Define L_{ij} as the correlated loss they generate when two related risks i and risk j occur simultaneously, obviously $L_{ij} = L_{ji}$.

Choquet integral, as a kind of fuzzy integral, is now widely used in decision analysis, data mining, and other fields. It can effectively solve the problem of interaction between attributes, that is, integrating the correlation information into the decision analysis process involving attributes through the fuzzy measure of fuzzy sets, so it can be used to measure the loss of risk correlation (the decision attribute at this point is the risk loss). From the Choquet integral, the integration operator at this point is equivalent to L_{ij}, that is, we have

$$\begin{aligned} L_{ij} &= \frac{\mu_i * \Delta L + \Delta\mu_i * L}{\mu_i * L}, \\ \Delta\mu_i &= \mu_i - \mu_{i+1}. \end{aligned} \tag{6}$$

μ_i denotes the fuzzy measure of the fuzzy set consisting of the ith risk, which is under the fuzzy measurement based on

$$\Delta\mu_i = \omega_i + \sum_{i=1}^{n} \left(I_{ij} - I_{ji} \right). \tag{7}$$

Based on the derived loss-at-risk values and incorporating them into the risk decision model, REC is defined as the expected value of risk loss considering correlated losses, then according to the definition is specified as follows:

$$R_{i\,d} = \sum_{i=1} I_{ij} \times \left[\frac{\left(1 - x_i\right)\left(1 - x_j\right)}{L_{ij}} \right], \tag{8}$$

where W denotes the set of correlated risks, $i, j \leq W$ means that risk i and risk j are correlated. Since x_{i} and x_{j} can only take 0 or 1, there is no correlation as long as at least one risk of x_{i} or x_{j} is controlled, that is, at least one of x_{i} or x_{j} has a value of 1. In addition, correlated risk losses include not only losses caused by themselves but also losses from correlations between their risks. In order to further analyze the changes of the model before and after considering correlation, the multiobjective risk decision model of the project without considering correlation is compared with the multiobjective risk decision model of the project considering correlation at the loss level, and the differences are shown in Table 1 below:

Table 1: Comparison of models with and without correlation.

Multiobjective risk decision model		Model 1	Model 2
Same point		1. Decision variables and risk assessment values 2. Minimize risk control cost targets 3. Models are integers	
Differences	Losses are nonadditive	No	Yes
	Different types of risk losses	But the risks	Related risks

As can be seen from the table, the multiobjective risk decision model under consideration of correlation is more complete, taking into account not only the impact of its own individual risk loss, but also the impact of risk loss related to it, which is also more relevant to the actual situation. According to the expression of risk-loss expectation:

$$\mathrm{RE}_i = P_i \otimes L_i. \tag{9}$$

The correlation between risk factors can be analyzed at the loss level and at the probability level. Since the model mentioned in this chapter places more emphasis on the probability of the occurrence of risks, the correlation between risks is analyzed only for the probability level to portray the correlation between risks. When there is a certain correlation between two risks, the occurrence of one risk will facilitate or inhibit the occurrence of the other risk to some extent, which is expressed in probability as the probability of occurrence of one risk will be influenced by the probability of occurrence of its related risk, and this logical relationship can be expressed by conditional probabilities, which can be obtained by solving Bayesian networks. Dynamic Bayesian network introduces time series on the basis of the original static Bayesian network, and through its own prior network and transfer network can get the conditional probabilities of nodes at different moments in time effectively. Since the dynamic Bayesian network itself is more complex, in order to simplify its inference process, it is generally necessary to attach some assumptions to the dynamic Bayesian network to simplify the calculation.

3.4. Variables in the Nodes. Under the aforementioned assumptions, a set of variables $y = \{y_1, y_2, \ldots, y_n\}$ is defined as n hidden nodes, and a set of variables $z = \{z_1, z_2, \ldots, z_n\}$ is defined as n observation nodes, and a static Bayesian network with n hidden nodes corresponding to n observation nodes is established, in which there is a logical relationship between hidden nodes and observation nodes, and between observation nodes and observation nodes. The probability distribution of the hidden nodes can be obtained by using the conditional probability through the observation values of the observation nodes. Based on the aforementioned definition, the prior network as shown in Figure 2 can be constructed, and the prior probability of each node can be obtained through the prior network, and the interaction between different risk factors will produce different prior networks.

Both risk-related multiobjective decision models at the loss level and probability level reflect multiobjective optimization problems. Traditionally, multiobjective optimization problems are solved by converting multiple objectives into a single-objective using classical methods, such as linear weighting method, constraint method, and maximum-minimum method. Although these traditions are simple to operate, they exhibit the following limitations when the multiobjective optimization objectives are in conflict.

(1) Using traditional methods to solve each algorithm can only get one Pareto optimal solution, and the merit of the solution is directly related to the parameters used in the multiobjective transformation of a single objective, while in practical application, multiple Pareto optimal solutions are often needed for decision-makers to make a choice, so that each time to obtain multiple Pareto optimal solutions requires constant adjustment of parameters, resulting in a lot of time consuming.

(2) The traditional method needs to combine multiple objectives, which requires the decision maker to have a high a priori knowledge of the optimization problem and due to the different parameter settings will generally produce different Pareto optimal solutions, if the decision maker has little background knowledge of the research problem, improper parameter settings will lead to poor quality of the obtained Pareto optimal solutions.

(3) Unlike traditional solution methods, the optimal solution obtained by the multiobjective particle swarm algorithm (MOPSO) is not unique, but a set of noninferior solutions, and each iteration produces a set of noninferior solutions that can be used for the next iteration, avoiding the trouble of resetting the parameters for each operation.

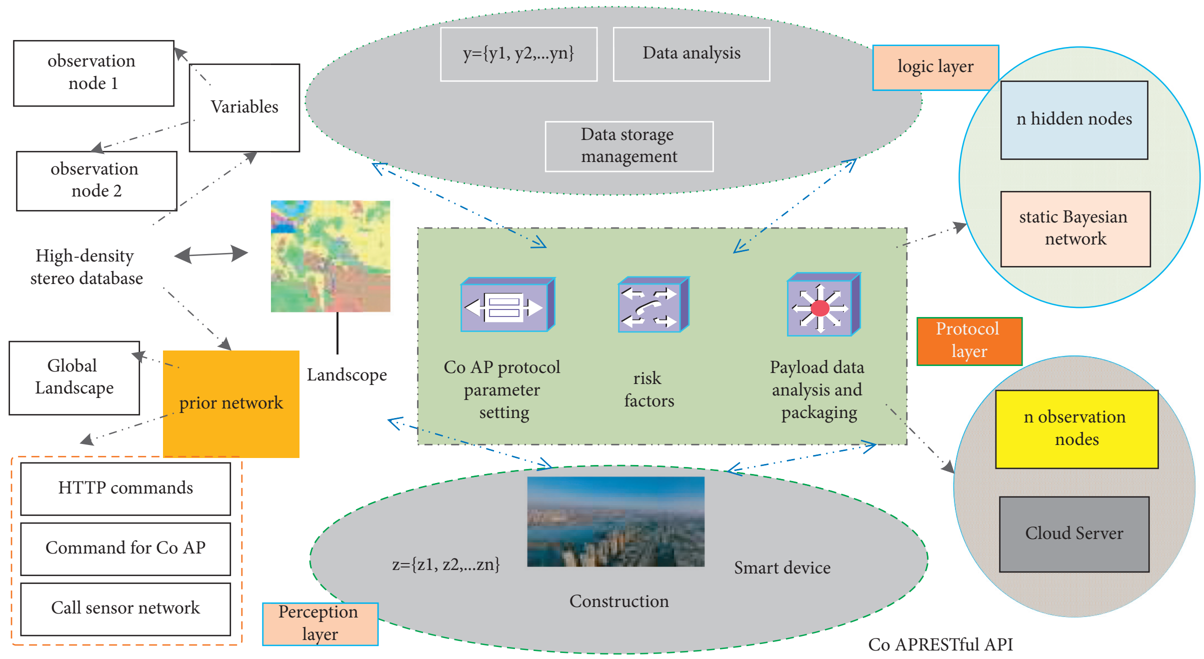

Figure 2: Dynamic Bayesian prior network.

In addition, the multiobjective particle swarm algorithm does not have high requirements on the problem itself, and its solution distribution and approximation are better, which makes the multiobjective particle swarm algorithm more suitable for solving multiobjective problems than the traditional multiobjective algorithm, as shown in Figure 3. In the multiobjective decision model of this paper, since minimizing the cost of risk control and minimizing the loss expectation of risk are two conflicting objectives, how to weigh their optimal can be achieved by multiobjective particle swarm algorithm.

4. Optimization and Risk Controlling

4.1. Optimization of Risk and Decision-Making. Risk loss expectation and risk control cost show some nonlinear relationship, and it can be seen that the risk loss expectation will gradually decrease with the increase of risk control cost, and when the control cost is equal to 0, which means that all risks are chosen not to be controlled, the corresponding risk loss expectation reaches the maximum value; conversely, as the risk control cost gradually increases, the risks are gradually controlled, which shows conversely, as the risk control cost gradually increases, the risk is gradually controlled and the risk loss expectation slowly decreases, and when the risk control cost increases to the maximum value, the risk loss expectation equals 0, which means that all risks are controlled at this time. However, in real life, it is almost impossible to control all risks, so decision-makers need to choose to control one or more risks based on the existing risk control cost to achieve the best risk control effect, so as to ensure that the resulting losses are minimized, as shown in Table 2.

Through further investigation and based on the results of expert evaluation, three pairs of correlated risk sets were identified, among which two pairs were positively correlated and one pair was negatively correlated, as shown in Figure 4. By comparing the loss caused by a single risk with the loss caused by two risks occurring at the same time, it is found that when the two risk factors "unreasonable design change requirements" and "damage to the substructure" occur at the same time, the unreasonable design will often change. There must also be cost loss in the whole process from design change determination to implementation, such as the coordination cost between the contractor and the builder, so when both of them occur at the same time, the loss sum generated by them is larger than the loss sum generated by them alone, showing a positive correlation; when the "engineer's approval delay" and the "construction damage" occur at the same time, there is a positive correlation. When the two risk factors of "engineer's approval delay" and "schedule delay" occur at the same time, on one hand, the schedule delay occurs not only from the various delays approved by the engineer but also from other reasons, such as technical reasons, resource allocation reasons, environmental reasons, and so on; on the other hand, for the critical path in the. On the other hand, the delay caused by the engineer's approval of the process on the critical path directly affects the schedule delay. The two are mutually inclusive relationship, so when the two occur at the same time, they produce losses and smaller than the losses and occur separately, showing a negative correlation.

The model is solved by applying the MOPSO algorithm again considering the risk-loss correlation, and 18 Pareto optimal solutions are obtained. It can be found that compared with the Pareto optimal solution set without considering correlation, although the number of solution sets remains the same, the optimal solution values change. By comparing the results of solving the model with and without considering correlation, the Pareto optimal solution set

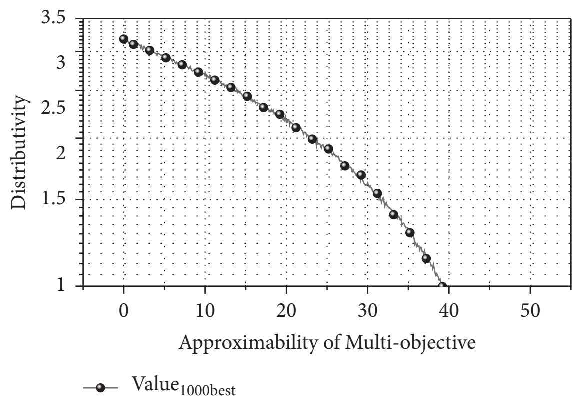

FIGURE 3: Distributivity and approximability of multiobjective particle swarm algorithm.

TABLE 2: Risk control effectiveness.

Risk nodes	Risk loss expectation	Risk control costs
Node 1	NA	0.4739 ± 0.157
Node 2	NA	0.5652 ± 0.148
Node 3	0.6213 ± 0.269	0.6220 ± 0.169
Node 4	0.6349 ± 0.253	0.6539 ± 0.165
Node 5	0.7365 ± 0.183	0.8186 ± 0.129

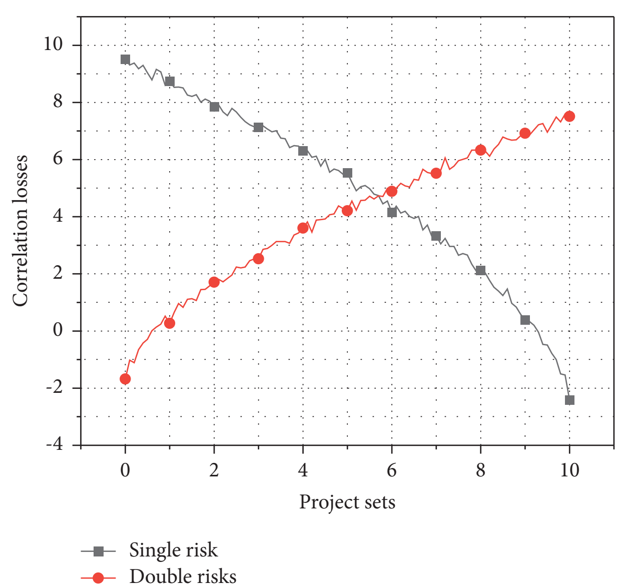

FIGURE 4: Correlation of construction project risk sets and correlation losses.

before and after considering correlation, that is, the image of the relationship between risk control cost and risk loss expectation, can be made, as shown in Figure 5.

4.2. Model Detection and Decision Optimization. At a certain risk control cost, the expectation of risk loss under consideration of correlation is much larger than the expectation of risk loss without consideration of correlation, and the increasing trend is slightly moderated in the interval [104, 2×104); in the interval [2×104, 3.6×104], the gap between the two gradually decreases and eventually reduces to zero. The reason for this trend is that the risk control cost held in the first two intervals is relatively small compared to the third interval, and thus the risk loss caused by considering correlation is greater, so that the first two intervals show more of a positive correlation between the two risks; while for the third interval because there is already sufficient risk control cost to gradually control the risk, the consideration of the correlation does not have a significant impact on the risk loss expectation, and the difference between the two decreases to zero. It can be seen that if the risk correlation is ignored, there will be certain differences before and after the model because only the loss caused by a single risk is

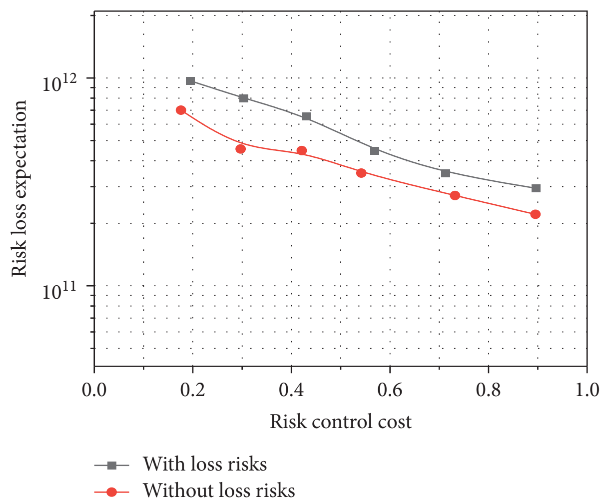

Figure 5: Relationship between risk control cost and risk loss expectation before and after considering loss risk correlation.

considered without considering the correlation loss, resulting in the risk loss expectation not greater than the risk loss expectation under the consideration of correlation, which means that the loss caused by the occurrence of risk is underestimated, and thus the assessment of construction project risk is not accurate. In this section, a multiobjective risk decision model is established by considering the loss correlation to measure the risk correlation from a quantitative perspective, so as to improve the risk management of construction projects. Similarly, the multiobjective particle swarm algorithm is applied to solve the model, and the parameter sets are all the same as those set. The results are compared with those obtained using static Bayesian network, and the results are shown in Figure 6. It is found that 13 Pareto optimal solutions can be obtained after several iterations, but there are some differences between the optimal solutions of both. The two aforementioned models only portray the correlation of risks from two different perspectives; the loss-level risk-related multiobjective decision model considers loss correlation, while the probability-level risk-related multiobjective decision model considers probability correlation, and there is no difference between the two.

From Figure 7, we can see that regardless of whether dynamic Bayesian network or static Bayesian network is used, the risk loss expectation and risk control cost of construction projects show an approximately nonlinear relationship, and the risk loss expectation gradually decreases with the increase of risk control cost; not only that, when the risk control cost is less than $15,000, it leads to a larger risk loss expectation because the control cost invested in risk is less. The risk loss expectation under dynamic Bayesian network is larger than that under static Bayesian network, which indicates that using static Bayesian network to estimate the risk probability will underestimate the loss caused by the risk; when the risk control cost is larger than $15,000, the risk is gradually controlled as the risk control cost increases, and at this time, no matter using dynamic Bayesian network When the risk control cost is greater than $15,000, the risk is gradually controlled as the risk control cost increases, at which time the difference between the two risk exposure values gradually decreases and eventually tends to zero regardless of whether the dynamic Bayesian network or static Bayesian network is used.

4.3. Network Algorithm Clustering Results. In practical situations, risks are often controlled in order to effectively prevent and avoid the occurrence of risks, but the economic conditions such as cost constraints often prevent the implementation of control for all risks. By solving the Pareto optimal solution obtained from the model, it is possible to select the appropriate decision solution based on the available risk control cost, that is, selectively control certain risks, such as risk avoidance, risk prevention, and risk transfer, while implementing measures such as risk retention for the uncontrolled risks. For the aforementioned example, assuming that there is only 6000 USD risk control cost, then the best decision is to control only the risk of "schedule delay", with specific measures such as strengthening construction supervision and management, establishing a sound project organization job responsibility system, and so on, so that the maximum return can be achieved with limited cost, as shown in Figure 8.

The two aforementioned models only portray the correlation of risks from two different perspectives; the loss-level risk-related multiobjective decision model considers loss correlation, while the probability-level risk-related multiobjective decision model considers probability correlation, and there is no difference between the two. However, either model considers correlation, which improves the accuracy and applicability of the model compared to the existing multiobjective risk decision models that do not consider correlation. The aforementioned examples show that the results obtained by the two models are still relatively close, and the risk loss expectation and the risk control cost both show an approximately nonlinear relationship, with a decreasing trend of the risk loss expectation as the risk

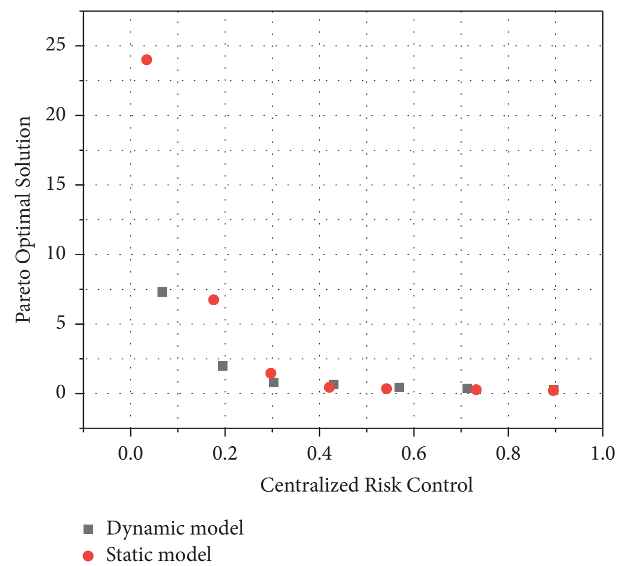

Figure 6: Comparison of Pareto optimal solution for dynamic Bayesian network and static Bayesian network with centralized risk control objectives.

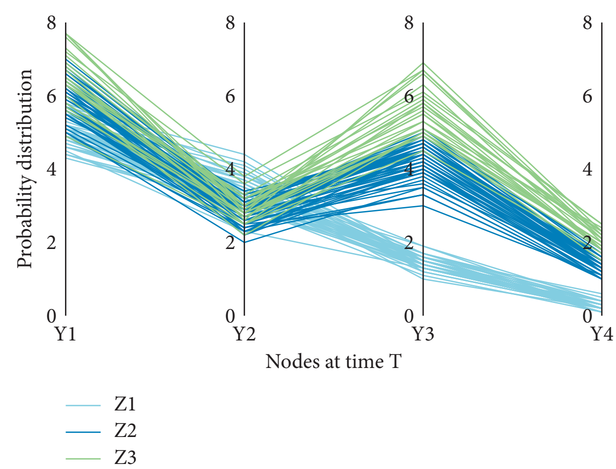

Figure 7: Probability distribution of nodes at time T.

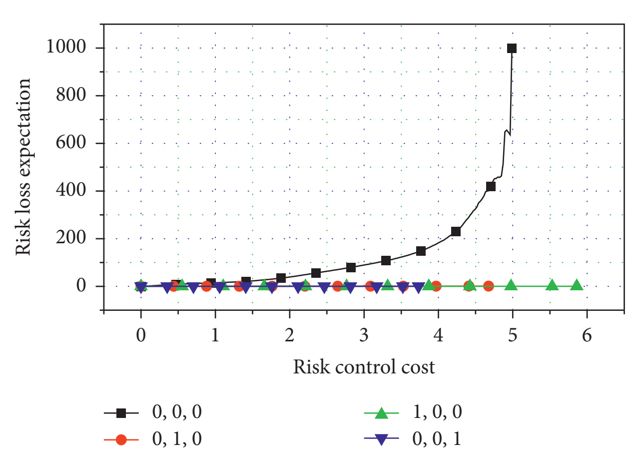

Figure 8: Risk control cost and risk loss expectation under the optimal solution.

control cost increases. When the probability of risk occurrence cannot be estimated by the lack of historical data, the loss-level risk-related multiobjective decision model can be used, and the model can be solved by the risk evaluation value obtained from the expert assessment and the existing risk control cost, and then the decision solution can be obtained for risk decision; when the probability of risk occurrence can be estimated by the sufficient historical data, the probability-level risk-related multiobjective decision. When the historical data are sufficient to estimate the probability of risk occurrence, the risk-related multiobjective decision model can be used to make risk decisions and achieve dynamic risk management using dynamic Bayesian networks.

5. Conclusion

In this paper, we apply the loss-level risk-related multiobjective decision model and the probability-level risk-related multiobjective decision model to a specific example and solve the risk control problem reflected by the example with a multiobjective particle swarm algorithm and find that there are some differences between the multiobjective risk decision model with risk correlation and the multiobjective risk decision model without risk correlation. In addition, the multiobjective risk decision model based on dynamic Bayesian network has higher risk assessment accuracy than the multiobjective risk decision model based on static Bayesian network, and the decision solution obtained from the model solution helps risk managers to make scientific and effective decisions to ensure that the risk loss is minimized with limited risk control cost. Compared with other decision models of construction projects, the decision model of construction projects in this paper takes into account the existence of certain correlation between risks, and tries to portray risk correlation from different perspectives such as the probability of risk occurrence and the loss caused by risk and establishes a multiobjective decision model that takes into account risk correlation to enhance the applicability and accuracy of the model, so as to provide some practical risk assessment and decision-making. The two models with or without risk correlation present certain differences, the model with correlation considered is more accurate and applicable than the model without correlation considered in the existing research, and compared with the static Bayesian network, the dynamic Bayesian network can improve the accuracy of estimating the risk probability of construction projects, can better explain the correlation between risks, and its results can more correctly reflect the results can more correctly reflect the actual situation of construction project risk management, thus improving the risk decision management. In the future, 13 Pareto optimal solutions can be obtained after several iterations, but there are some differences between the optimal solutions of both.

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 known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the 'Key Art Projects of the National Social Science Foundation (grant no.18AH008)'.

References

[1] S. Antomarioni, M. M. Bellinello, M. Bevilacqua, F. E. Ciarapica, R. F. D. Silva, and G. F. M. D. Souza, "A data-driven approach to extend failure analysis: a framework development and a case study on a hydroelectric power plant," *Energies*, vol. 13, no. 23, pp. 6400–6421, 2020.
[2] X. Gou, Z. Xu, W. Zhou, and E. Herrera-Viedma, "The risk assessment of construction project investment based on prospect theory with linguistic preference orderings," *Economic Research-Ekonomska Istraživanja*, vol. 34, no. 1, pp. 709–731, 2021.
[3] A. Ghasemof, M. Mirtaheri, R. K. Mohammadi, and M. R. Mashayekhi, "Multi-objective optimal design of steel MRF buildings based on life-cycle cost using a swift algorithm," *Structures*, vol. 34, pp. 4041–4059, 2021.
[4] F. Ghodoosi, A. Bagchi, M. R. Hosseini, T. Vilutienė, and M. Zeynalian, "Enhancement of bid decision-making in construction projects: a reliability analysis approach," *Journal of Civil Engineering and Management*, vol. 27, no. 3, pp. 149–161, 2021.
[5] P. Jiang, Z. Liu, J. Wang, and L. Zhang, "Decomposition-selection-ensemble forecasting system for energy futures price forecasting based on multi-objective version of chaos game optimization algorithm," *Resources Policy*, vol. 73, Article ID 102234, 2021.
[6] M. Ehsanifar and M. Hemesy, "A new hybrid multi-criteria decision-making model to prioritize risks in the construction process under fuzzy environment (case study: the Valiasr Street underpass project)," *International Journal of Construction Management*, vol. 21, no. 5, pp. 508–523, 2021.
[7] B. Liu and D. Rodriguez, "Application of multi-objective optimization model to assess the energy efficiency measures for the cases of Spain," *Journal of Building Engineering*, vol. 38, Article ID 102144, 2021.
[8] X. Xu and P. X. W. Zou, "System dynamics analytical modeling approach for construction project management research: a critical review and future directions," *Frontiers of Engineering Management*, vol. 8, no. 1, pp. 17–31, 2021.
[9] X. Ren, Y. Wu, D. Hao, G. Liu, and N. Zafetti, "Analysis of the performance of the multi-objective hybrid hydropower-photovoltaic-wind system to reduce variance and maximum

power generation by developed owl search algorithm," *Energy*, vol. 231, Article ID 120910, 2021.

[10] M. S. Sanaj and P. M. Joe Prathap, "Nature inspired chaotic squirrel search algorithm (CSSA) for multi objective task scheduling in an IAAS cloud computing atmosphere," *Engineering Science and Technology, an International Journal*, vol. 23, no. 4, pp. 891–902, 2020.

[11] A. Seifi, M. Ehteram, and F. Soroush, "Uncertainties of instantaneous influent flow predictions by intelligence models hybridized with multi-objective shark smell optimization algorithm," *Journal of Hydrology*, vol. 587, Article ID 124977, 2020.

[12] Z. Shao, F. Si, H. Wu, and X. Tong, "An agile and intelligent dynamic economic emission dispatcher based on multi-objective proximal policy optimization," *Applied Soft Computing*, vol. 102, Article ID 107047, 2021.

[13] A. Qazi, A. Daghfous, and M. S. Khan, "Impact of risk attitude on risk, opportunity, and performance assessment of construction projects," *Project Management Journal*, vol. 52, no. 2, pp. 192–209, 2021.

[14] Y. Song, K. Zhang, X. Hong, and X. Li, "A novel multi-objective mutation flower pollination algorithm for the optimization of industrial enterprise R&D investment allocation," *Applied Soft Computing*, vol. 109, Article ID 107530, 2021.

[15] R. Syah, S. Faghri, M. K. Nasution, A. Davarpanah, and M. Jaszczur, "Modeling and optimization of wind turbines in wind farms for solving multi-objective reactive power dispatch using a new hybrid scheme," *Energies*, vol. 14, no. 18, pp. 5919–5926, 2021.

[16] C. E. Obodo, Z. Xie, B. B. Cobbinah, and K. D. Y. Yari, "Evaluating the factors affecting contractors tender for project construction: an empirical study of small scale indigenous contractors in awka, Nigeria," *Open Journal of Social Sciences*, vol. 9, no. 7, pp. 381–397, 2021.

[17] X. Wang, X. Mao, and H. Khodaei, "A multi-objective home energy management system based on internet of things and optimization algorithms," *Journal of Building Engineering*, vol. 33, Article ID 101603, 2021.

[18] C. Xie, D. Y. Lin, and S. T. Waller, "A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies," *Transportation Research Part E: Logistics and Transportation Review*, vol. 46, no. 3, pp. 295–316, 2010.

[19] J. Zhang, Y. Huang, G. Ma, Y. Yuan, and B. Nener, "Automating the mixture design of lightweight foamed concrete using multi-objective firefly algorithm and support vector regression," *Cement and Concrete Composites*, vol. 121, Article ID 104103, 2021.

[20] D. Chenger and J. Woiceshyn, "Executives' decision processes at the front end of major projects: the role of context and experience in value creation," *Project Management Journal*, vol. 52, no. 2, pp. 176–191, 2021.