Research on Deepening and Optimizing the Special Plan for Deep Excavation Based on Subway Engineering Site Information

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Abstract. This article aims to optimize the safety measures of the special plan and proposes a Bayesian network method for modeling the safety risks of construction sites based on construction site information. It transforms the optimization problem of safety measures into a dynamic combination problem of safety measures and introduces a genetic algorithm to solve this combination optimization problem. Improving the safety level of the subway construction site has reduced the construction risk factors.

Keywords: Construction Technical Plan for Safety; Multi-objective Optimization Modeling.

1. Introduction

The construction environment of deep foundation pits in subway stations is complex and requires high technical requirements, which is the focus of station construction safety management. In order to ensure the safety of deep foundation pit construction, it is necessary to prepare a special safety plan to guide the construction. Due to the special plan being formulated before construction, the static special plan formulated before construction still lacks targeted consideration for the dynamic changes on the construction site, although some consideration has been given to the dynamic changes on the construction site during guidance.

By referring to similar projects in the past, developing a new plan can significantly improve the performance of the new plan on the construction site[1]. Thomas and Ellis[2] discussed the issue of effective pre bidding planning for small and medium-sized contractors in the current limited literature. Menches and Hanna[3] studied that in the context of fierce market competition, contractors tend to specify a better solution as a way to improve efficiency and increase profits. Menches et al. [4]studied that a better solution can become an effective way to improve efficiency and increase profitability when the project profit level is low. This study proposed a process model for formulating power engineering construction plans and also proposed evaluating the effectiveness of plan formulation by comparing actual plans with the model process. In the process of guiding engineering with special plans, appropriate methods are needed to consider the situation of the construction site to dynamically deepen and optimize the special plan[5]. Security measures, also known as risk control measures, are one of the important contents in special plans and the most important optimization content to pay attention to under the dynamic and changing characteristics of the site.

2. Construction of a Safety and Risk Resistance Model Based on Construction Sites

2.1 Risk Identification of Subway Deep Foundation Pit Construction

Risk decomposition structure of deep foundation pit engineering in subway stations. This article mainly combines accident statistics and literature review to analyze safety risks and obtain the risk decomposition structure of subway stations. Accident statistical analysis shows that during the construction process of subway stations, there is a high risk of damage to the surrounding environment, collapse of foundation pits, instability of supports, sand flow in pipes, and other risks (including falling from heights, object impact, electric shock, mechanical injury, and fire). Through the analysis of relevant literature on safety risks in the construction of open cut subway stations, it is found that there may be risks of surrounding environmental damage, foundation pit collapse, underground continuous wall collapse, foundation uplift, foundation pit surge, support instability, as well as other risks such as falling from heights and object impact during the construction process of open cut subway stations. Based on the above analysis, the main risk analysis of the construction process of open cut subway stations is as follows:

1) Risk of damage to the surrounding environment R1. During the construction process of subway stations, factors such as excessive precipitation and pipeline leakage can cause damage such as tilting and cracking of surrounding buildings, roads, and underground pipelines. Therefore, it can be subdivided into three types of risks: surrounding building damage risk R11, pipeline damage risk R12, and ground collapse risk R13.

2) Risk of collapse of enclosure structure R2. The main risk of collapse during the construction of the retaining structure itself includes the risk of ground wall collapse R21, drilling pile collapse R22, and rotary jet grouting pile collapse R23.

3) Risk of foundation pit collapse R3. During the construction of subway stations, there is a risk of foundation pit collapse due to factors such as top loading, over excavation of soil, and untimely support. The risk of foundation pit collapse can be further divided into the risk of foundation pit enclosure structure collapse, foundation pit soil collapse, and support frame collapse.

4) The risk of seepage in the enclosure structure is R4. Due to the presence of cracks and other issues in the enclosure structure, the water stop effect is not poor, causing water carrying sand particles to rush into the pit from the cracks, posing a risk of damage to the enclosure structure.

5) Risk of basal uplift R5. In the soft clay layer, due to the squeezing effect of the soil outside the excavation pit after excavation, the wall moves inward, which poses a risk of the soil below the excavation pit lifting upwards.

6) Risk of sand flow in pipes R6. During the construction process of subway stations, if there is a water head difference in the pit and the self-weight of the soil is less than the water head pressure, it often causes the risk of pipe surge and sand flow.

7) Support instability risk R7. During the construction process of the station, as the earthwork is excavated, the force on the horizontal support gradually increases. If the assumption of the lower horizontal support is not timely, the slenderness ratio of the vertical support increases, and the quality of the support construction is poor, there will be a risk of support instability.

8) Other risks R8. Other risks include the risk of falling from heights due to inadequate protective measures such as "three treasures, four entrances, and five edges", object strikes caused by falling objects from heights, machine injuries caused by improper mechanical operation, electric shock, and fire risks.

Among them, risks such as R1-R4, R6, and R7 are closely related to the engineering environment and belong to major risk management points in engineering. There are many and complex risk factors that require special attention [6]; The risks included in category R5 belong to general risks, and the risk mechanism is relatively clear and simple. Effective management can be achieved by using common safety measures. This study mainly discusses and analyzes the previous types of risks. Based on the different objects guided by the special construction plan for the safety of deep foundation pits in subway stations and the possible risk events that may occur during the process, the WBS and RBS risk identification matrices have been constructed.

2.2 Risk Assessment of Construction Site based on Bayesian Network

Based on the Bayesian risk network of deep excavation construction sites in subway stations, risk resistance analysis can be conducted on specific projects. The risk resistance evaluation mainly includes comprehensive risk resistance evaluation and identification of key risk factors.

Specific project risk resistance evaluation. In the construction site, safety measures at the management and technical levels are closely related to the occurrence status of risk events at the construction site. Generally speaking, the more comprehensive and complete the on-site safety measures are, the lower the probability of safety risks occurring at the construction site; On the contrary, the probability of security risks occurring is higher. Due to the relationship between security risks and management and technical aspects, security risks exhibit certain regional characteristics. Taking a certain designated area as an example, through expert experience and corresponding management norms, standards, and other literature materials. Therefore, based on the Bayesian network model of the construction site, the values of risk factors are calculated to obtain the safety and risk resistance ability of the construction site[7]. Using Bayesian networks, based on the probability of occurrence of construction site risk factors and CPT obtained from surveys, the parent node event P (R=1) can be calculated, with the formula:

$$P(R=1)=\sum(P(R=1\mid X_i=x_i)\times P(X_i=x_i)), i=1,2,...,n \tag{1}$$

In the formula, n represents the number of child nodes, and the probability interval for each node is [0,1], which represents the probability value of the node from occurrence to non occurrence. The value of P (R=1) represents the likelihood of risk R occurring.

Identification of key risk factors for the project to be evaluated. By using BN's reverse inference technology, the posterior probability P (X=1 | R=1) of risk factors in the event of an accident can be analyzed. The larger the probability value, the greater the possibility that the node is called the one causing the risk event to occur. It should be controlled as a key factor during the construction process, and the calculation formula is as follows:

$$P(X_i=1\mid R=1)=\frac{P(X_i=1)\times P(R=1\mid X_i=1)}{P(R=1)}, i=1,2,...,n \tag{2}$$

In the formula, P (X=1 | R=1) is the posterior probability of occurrence of the risk factor. Through the above evaluation, it is possible to effectively identify the risk factors that should be emphasized on the construction site, and evaluate the safety and risk resistance ability of the construction site based on the construction site situation, providing a basis for deepening and optimizing risk control measures in the next step. Bayesian networks can clearly describe the relationship model between events and factors. Compared with the black box prediction and evaluation of neural network models, Bayesian networks have good comprehensibility and logicality[8]. Secondly, Bayesian network inference has low requirements for existing information and is suitable for risk evolution inference in deep excavation engineering sites with incomplete and uncertain information.

3. Dynamic Optimization Model for Construction Safety Special Plan

This study defines the impact of safety measures on construction period and cost as the Construction Period Impact Index ($t(s_j)$) nd Cost Impact Index ($c(s_j)$), respectively. The duration index ($t(s_j)$) refers to the increased duration of the safety measures taken during implementation and the impact of these measures on the progress of subsequent process activities; Understanding it as the proportion of increasing the construction period to the total construction period, the larger the proportion, the greater the impact; The smaller the proportion, the smaller the impact; The general value range is [0,1]: Cost index ($c(s_j)$),refers to the cost impact of implementing safety measures: understood as the proportion of increased costs to the total construction period, the larger the proportion, the greater the impact, and the smaller the proportion, the smaller the impact; The range of values is [0, 1]. The issue of selecting security measures can be understood as minimizing the impact of a combination of security measures while meeting the control of risk factors[9]. Further analysis of the above issues can express the objective function of the optimization model for selecting safety measures as: how to combine safety measures to minimize the impact of safety measures on construction period and cost. The constraint is expressed as: how to choose a combination of safety measures to control risk factors, that is, within the control objectives. So, the multi-objective optimization model for security measures is constructed as follows:

$$\min\ Q = w_1 \sum_{j=1}^{n} k_j \times c(s_j) + w_2 \sum_{j=1}^{n} k_j \times t(s_j) \tag{3}$$

$$s.t.\begin{cases} P\left(\dfrac{x_i}{s_j}\right) = p(x_i) \times \sum k_j \times \Pi(1-a_{ij}) \\ P(a) = \sum p\left(\dfrac{x_i}{s_j}\right) p\left(\dfrac{a \cdot s_j}{x_i}\right), i=1,2,...,n; j=1,2,...,m \\ P(a) \le P'(1-\eta) \\ k_j = \begin{Bmatrix} 1, s_j \text{ is selected ;} \\ 0, \text{ otherwise} \end{Bmatrix} \end{cases} \tag{4}$$

In the formula: s_j represents safety measure j; $c(s_j)$ and t (s_j) represent the cost index and duration index of safety measures s_j, respectively; The range of values for both is [0, 1]; Q is the comprehensive impact index of safety measures s_j; k_j For safety measures s_j; Whether to be selected as a variable, k_j $=\{0,1\}$; w_1 and w_2 represent the weights of cost index and duration index in the objective function, reflecting the preferences of different decision-makers towards the decision objectives; a_{ij} is the matrix value of the factor risk measure relationship, which means when the risk measure s_j; Post adoption risk factor x_i; The degree of reduction in the probability of occurrence, with a value range of [0, l]. P $(x_i / s_j;)$ is the current security risk measure s_j; Adopt risk factors x_i under implementation; Probability of occurrence; P (R) is the probability of risk events occurring after the implementation of safety risk measures; P' is the warning value for the occurrence of risk events; It is a safety redundancy in the occurrence of risk events.

4. Optimization Model Solution Based on Benetic Algorithm

The steps to apply genetic algorithm are as follows[10]:

(1)Initialization: Initialize the generation gen=0 and set the maximum evolution generation T, randomly generating N individuals as the initial population P. For the optimization problem of security measure selection, security measure selection is a typical Boolean value, defined as the vector X=(x_1, x_2, x_3, ... x_j , ... x_m), where x_j $=\{0,1\}$, j=1, 2, ... m. As a chromosome, it serves as a safety measure to optimize the possible solution of the combination scheme.

(2) Individual evaluation: Calculate the fitness values of each individual in group P. To calculate the fitness value, it is necessary to choose the fitness rain number. The fitness function is determined based on the objective function to indicate the superiority or inferiority of an individual or solution, and is the basis for selection operations. Due to the non negativity of the fitness function, this paper adopts the fitness function Fit=c_{max}-F (x), where c_{max} is a positive number of 1.

(3)Selection operation: Apply the selection operator (P_s) to the population, directly inheriting the optimized individual to the next generation. The selection operation is based on the fitness value of individuals in the population, and a certain proportion of chromosomes can be selected to be retained in offspring according to the fitness value, which is called the selection operator P_s.

(4) Cross operation: Apply the crossover operator (P_c) to the population to generate new individuals by counting the number of chromosomes participating in the crossover in the case pool. P_c is generally ranging from 0.4 to 0.99, and a suitable crossover operator can effectively control the degree of individual crossover in the case pool, meeting the needs of crossover.

(5) Mutation operation: Applying the mutation operator (P_m) to a population is the process of gene mutation on chromosomes, which changes one or some positions on an individual's coding string with a small probability. For example, in binary coding, "0" becomes "1", "1" becomes "0", and new genes are produced. After combining mutation with selection and crossover, certain information loss can be avoided, ensuring the effectiveness of genetic algorithms. P_m is generally taken as 0.0001-0.1. Group p, t_i; After selection, crossover, and mutation operations, the next generation population is obtained as t_{i+1}.

(6)Termination condition judgment: After multiple generations of evolutionary computation, until the objective function value tends to stabilize and converge, or reaches the set evolutionary algebra, terminate the computation, and output the objective value and problem solution.

In traditional genetic algorithms, the parameter crossover probability P and mutation probability Pm are often fixed and unchanged during the evolution process, and both affect the performance of genetic algorithms. To improve the performance of the optimization model, consider setting adjustment mechanisms for crossover probability and mutation probability, and set the following adjustment mechanisms:

$$p_{mi} = \begin{cases} p_{m\min} + (p_{m\max} - p_{m\min})\left(\dfrac{g}{2G} + \dfrac{f_i - f}{2\left(f_{\max} - \bar{f}\right)}\right) \\ f_i \geq \bar{f} \\ p_{m\ \min}\ , f_i < \bar{f} \end{cases} \tag{5}$$

$$p_{m\min} = \begin{cases} 0.001, g \leq G/4 \\ 0.002, G/4 < g \leq 3G/4 \\ 0.003, 3G/4 < g \leq G \end{cases} \tag{6}$$

Among them, P_{mi} is the probability of individual i undergoing mutation. From equations(5), it can be seen that individuals with smaller fitness function values have a lower probability of mutation, which leads to a similarity in the genetic structure of individuals in the population as the number of iterations increases, and may fall into local optima.. Setting $P_{m\ max}$=0.005, $P_{m\ min}$ adjusts with the number of evolutions, as shown in formula(6), indicating that in the early stages of evolution, the likelihood of individual variation is relatively low; In the late stage, increasing the probability of individual mutation operations in the population is beneficial for expanding the search range and jumping out of local optima. Based on the above approach, the objective function and constraint conditions are programmed, the candidate solutions are encoded in binary, and the optimal combination of safety measures that meet the safety risk control objectives is obtained through optimization. show the simulation analysis results of operator improved genetic algorithm and simple genetic algorithm (a, b, and c at different stages in the time dimension, respectively).

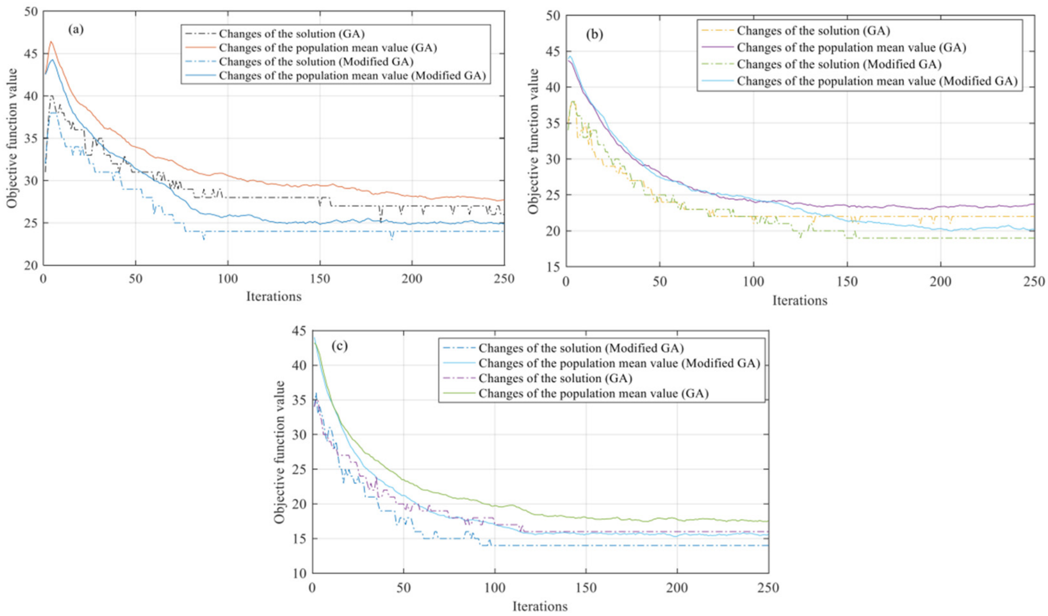

Fig 1. Comparison of results between operator based improved genetic algorithm and simple genetic algorithm

5. Summary

This article first analyzes the decision-making process of selecting safety measures for special plans, and clarifies that the selection of safety measures should consider the relevant constraints of management objectives. Then, the Bayesian network method is used to construct a risk event Bayesian network, and the occurrence of risk factors in the implementation of safety measures at the construction site is obtained. After that, the anti-risk ability evaluation of the construction site is carried out, and key risk factors and high sensitivity factors are identified in reverse, providing a basis for taking safety measures. On this basis, this chapter constructs a multi-objective optimization model for the selection of safety measures in special plans; Introducing genetic algorithm to code and solve the optimization problem, obtaining the optimal set of risk control measures for on-site safety management. The optimization method of specialized plan knowledge based on on-site information provides effective support for controlling construction risk factors and optimizing the selection of risk measures, improving the implementation effect of specialized plans.

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