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MULTI-RISK MANAGEMENT FOR UNDERSEA TUNNEL CONSTRUCTION BASED ON NSGA-III ALGORITHM

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Abstract: Due to the complexity of construction techniques, long construction periods, high investment costs, numerous safety-related factors, and stringent quality requirements, managing multi-source information in subsea tunnel projects often lacks coordination, making it difficult to achieve unified multi-objective goals. This poses a common challenge for construction decision-makers during on-site management. To address these gaps, this study focuses on safety, schedule, and cost risks in undersea tunnel construction, designing a multi-object model to address these challenges. By integrating the relationships among safety levels, schedule and cost across various construction processes, a multi-objective optimization model tailored to the management of complex undersea tunnel construction projects is proposed. The model is solved by the NSGA-III algorithm to obtain the Pareto solution set. This approach is applied to a subsea tunnel project, and the results show that when the number of generations is set to 600, the population size to 140, and the number of reference points per dimension to 14, a total of 170 solutions are obtained. Among them, the construction duration can be optimized by up to 132 days, and the cost by up to 110.58 million CNY, while both quality and safety levels remain within acceptable project limits. These results can assist decision-makers in selecting the optimal construction plan from multiple perspectives.

Keywords: Tunnel construction; Construction management; Multi-object optimization; NSGA-III algorithm

1. INTRODUCTION

The current scale of tunnel construction in China is enormous, but due to complex procedures, poor processes, and long construction duration, safety accidents frequently occur during tunnel construction. Compared to other underground engineering projects, tunnel projects are more prone to frequent safety accidents due to complex uncertainties (Zhao et al., 2007). These accidents not only cause delays in construction schedules, resulting in economic losses and quality defects but also lead to adverse societal impacts. How to comprehensively consider various types of losses derived from core safety risks to achieve optimal decision-sharing among multiple stakeholders is a challenge in the process of undersea tunnel construction.

The ideal scenario for undersea tunnel construction is to achieve the shortest construction period, the lowest cost, and the highest quality while maintaining safety risks at a low level - an outcome that is challenging to achieve in practical construction processes. Safety risks, construction period, cost, and quality are not independent factors; rather, they form an interrelated and contradictory unified system. Any change in one of these objectives inevitably impacts the levels of the others. As large-scale, high-risk engineering projects, undersea tunnels face the critical challenge of addressing and controlling safety risks during the construction process. However, there is a critical balance point between contractors' safety investment and cost control. When confronted with high safety risk levels, determining how to enhance risk detection and monitoring equipment to reduce safety risks to an acceptable level for contractors is a topic worthy of discussion (Bachar et al., 2025). In the field of multi-objective optimization for engineering projects, the relations9hip between cost and construction period has garnered the most attention from scholars and contractors. Metrics such as labor, labor utilization, and profit can serve as

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indicators for quantifying cost risks (Jun et al., 2010; Agrama et al., 2014), thereby enabling the establishment of relationships between project duration fluctuations and total cost demands (Parente et al., 2015; El-Abbasy et al., 2016). Compared to other risks, the relationship between safety and quality is often overlooked. However, in 2013, Wanberg, J. et al. (2013) demonstrated a correlation between quality performance and safety performance, developing a safety-quality correlation model. P. E. D. Love et al. (2023) also emphasized that balancing the competing demands of quality and safety in construction processes enables managers to minimize rework and improve project safety in an optimal manner. Nevertheless, the aforementioned studies generally focus only on the interactions between two risks. With the evolving societal demands, many scholars have begun to examine the interrelationships among multiple risks. Wang, T. (2023) developed a multi-parameter grey GERT model to discuss the functional relationships among time, cost, and quality in scenarios of both normal execution and rework, proposing a multi-objective joint optimization model based on schedule-oriented and quality-oriented approaches. Meng, F. (2024) introduced environmental impact into the analysis, constructing a multi-objective optimization model encompassing time, cost, safety, and environmental factors. However, most existing studies on multi-objective optimization models focus on general projects with fixed timelines and single-line engineering. Tunnel projects, characterized by their linear nature, complex procedures, and repetitive tasks, pose unique challenges to multi-objective optimization management.

In recent years, scholars have explored various challenges in solving algorithms for multi-objective optimization models. Currently, most research focuses on low-dimensional multi-objective optimization models with up to three objectives, utilizing algorithms such as Ant Colony Optimization, Genetic Algorithms, and NSGA-II (Xiong et al., 2007; Li et al., 2024). Among these, NSGA-II is widely regarded for its high computational efficiency and convergence performance, making it a popular choice in fields like project scheduling and construction period optimization (Zhang et al., 2021; Wu et al., 2022). However, despite the ability of NSGA-II to generate well-converged and evenly distributed solution sets, its original algorithmic capacity becomes insufficient as the number of objectives increases. The NSGA-III algorithm builds upon NSGA-II by introducing a reference point mechanism that retains non-dominated individuals close to the reference points. This makes NSGA-III better suited for solving high-dimensional multi-objective optimization models with more than three objectives (Dehghani et al., 2019; Liu et al. 2022; Razmi et al., 2022; Zhao et al., 2024).

In summary, research on balanced optimization models targeting safety-cost-schedule-quality in undersea tunnel construction projects is scarce, and studies addressing optimization algorithms for models with more than three objectives are also limited. To address these gaps, this study focuses on safety risk control in undersea tunnel construction to establish an inter-objective constraint model. By integrating the relationships among safety levels, schedule, cost, and quality across various construction processes, this study proposes a multi-objective optimization model tailored to the management of complex undersea tunnel construction projects. The model is solved using the NSGA-III algorithm.The proposed optimization model and NSGA-III algorithm are validated through a case study of an undersea tunnel project in China. This research offers a novel approach to addressing multi-objective optimization problems in undersea tunnel construction, providing a more effective framework for achieving optimal construction management outcomes.

2. MULTI-OBJECTIVE OPTIMIZATION MODEL FOR TUNNEL CONSTRUCTION

2.1 Safety Function

According to the national standard (GB50652-2011) *Code for Risk Management in the Construction of Urban Rail Transit Underground Works* (hereinafter referred to as the "National Standard"), safety risks are classified into five levels. Safety risks of different levels may lead to varying impacts on construction schedule and cost. For ease of coding, the safety risk level function is simplified as follows:

$$S = g(R_i) = \begin{cases} 1, & R_i = V \\ 2, & R_i = IV \\ 3, & R_i = III \\ 4, & R_i = II \\ 5, & R_i = I \end{cases} \tag{1}$$

Where Ri is derived from the risk level of safety incidents.

2.2 Schedule Function

By analyzing the relationship between all construction procedures during the tunnel construction process, the construction sequence is divided into multiple cycles, each consisting of several procedures with finish-to-start dependencies. Each procedure affects the others. Tunnel construction mainly includes two types of operations: excavation and pre-excavation grouting. During excavation, the time spent on excavation per cycle typically depends on the rock grade. The total grouting time depends on the required grouting length and the effectiveness of the grouting. Assuming each procedure in the construction process has a maximum acceptable operation time and a minimum achievable time, the objective function of the work is:

$$T_N = \sum_1^{N_P} \sum_{k=1}^{n_P} p_{P,k} * t_{P,k} + \sum_1^{N_E} \sum_1^{n_E} p_{E,k} * t_{E,k} \quad \text{s.t. } t_{min,i} \leq t_i \leq t_{max,i} \tag{2}$$

Where: T_N is the total duration of normal construction; $p_{P,k}$ is the proportion of grouting length in the total project; $t_{P,k}$ is the time required for grouting procedure k; $n_P$is the number of grouting operations; N_P is the total number of grouting operations in the entire project; $p_{E,k}$ is the proportion of different surrounding rock grades; n_E is the number of excavation operations; N_E is the total number of excavation cycles in the entire project; $t_{E,k}$ is the time required for excavation procedure; $t_{min,i}$ is the minimum time for procedure i; $t_{max,i}$ is the maximum time for procedure i.

In addition to the normal fluctuations in construction schedule, this study also considers the impact of safety risks on the schedule. The delay caused by safety risks typically depends on the risk level Ri It is assumed that the impact on the schedule is represented by a random number falling within the corresponding interval, as shown in Equation (3) and (4).

$$T_{ES,i} = f(R_i) = \begin{cases} [0,1), & R_i = V \\ [1,3), & R_i = IV \\ [3,10), & R_i = III \\ [10,90), & R_i = II \\ [90,+\infty), & R_i = I \end{cases} \tag{3}$$

$$T_E = \sum_{i=1}^{n} T_{E,i} \tag{4}$$

Where Ri is derived from the risk level of safety incidents, and TES,i is a random number falling within the corresponding interval.

Then, the total construction duration is:

$$T = T_N + T_E \approx \sum_1^{N_P} \sum_{k=1}^{n_P} p_{P,k} * t_{P,k} + \sum_1^{N_E} \sum_1^{n_E} p_{E,k} * t_{E,k} + \sum_{i=1}^{n} T_{E,i} \tag{5}$$

2.3 Cost Function

In general, the total construction cost of a project consists of the sum of direct and indirect costs. However, for tunnel projects with long construction durations and complex construction processes, various safety incidents may arise during construction. The potential consequences of these incidents—such as casualties, schedule delays, and direct economic losses—cannot be ignored. Therefore, this study incorporates safety risk factors into the cost function.

Direct costs mainly consist of labor, material, and equipment costs associated with each construction procedure and are directly related to specific construction activities. There is a direct relationship between the duration of a procedure and its cost: when the procedure time increases, the cost inevitably rises; conversely, shortening the duration (i.e., fast-tracking) often requires a substantial increase in resource input, which also raises costs. Thus, the relationship between direct cost and time is illustrated in Figure 1 and Equation (6) and (7).

$$C_{m,i} = C_{n,i} + \varphi_i (t_i - t_{n,i})^2 \tag{6}$$

$$C_M = C_N + \sum_{l=1}^{L} \varphi_i (t_i - t_{n,i})^2 \tag{7}$$

Where: $C_{m,i}$ is the adjusted direct cost of procedure i after marginal cost correction; $C_{n,i}$ is the direct cost of procedure i under normal conditions; φ_i is the marginal cost growth coefficient of procedure i; $t_{n,i}$ is the normal duration of procedure i; C_N is the originally planned direct cost.

During the construction process, indirect costs are incurred for construction management, contract administration, quality control, and other activities. These costs cannot be directly attributed to a specific construction task but are closely related to the overall project duration. Therefore, this study distributes the total indirect cost evenly across the entire construction process and approximates the total indirect cost as a linear function of the project duration, as shown in Equation (8).

$$C_J = \gamma T \tag{8}$$

Where, C_J represents the total indirect cost; γ is the indirect cost coefficient.

For tunnel projects with long construction durations and complex construction processes, numerous safety incidents may arise during construction. The occurrence of such incidents can lead to casualties, schedule delays, and direct economic losses, which cannot be ignored. Therefore, this study incorporates the unit cost under the influence of safety risks C_S into the cost function., as shown in Equation (9).

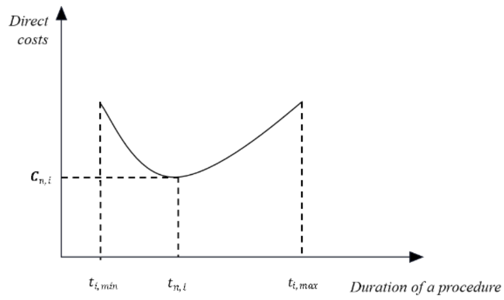
$$C_S = \varphi(Ri) \cdot [\sum C_{Sg,i} + \sum C_{Sf,i}] \tag{9}$$

Where: $\varphi(Ri)$is the safety risk impact coefficient; $C_{Sg,i}$ represents the direct loss caused by each safety risk level; $C_{Sf,i}$ represents the indirect loss caused by each safety risk level.

In summary, the total cost function can be expressed as:

$$C = C_N + \sum_{l=1}^{L} \varphi_i (t_i - t_{n,i})^2 + \gamma T + \varphi(R_i) \cdot [\sum C_{Sg,i} + \sum C_{Sf,i}] \tag{10}$$

Figure 1. *Function of direct costs and duration of procedure i*



2.4 Quality Function

When the duration of an individual task is either too short or too long, it cannot achieve optimal quality. Only within a certain range of duration can the task maintain a high level of quality with minimal variation. This pattern of quality fluctuation better reflects the actual conditions in engineering projects. This study assumes that the relationship between quality and excavation time follows a bell-shaped function, as illustrated in Figure 2 and Equation (11) and (12).

$$Q_i = exp(-\frac{(t_i - t_{i,mean})^2}{m*(t_{i,max} - t_{i,min})^2}) \tag{11}$$

$$Q = avg\ Q_i \tag{12}$$

Where: m is the coefficient representing the relationship between quality and schedule, determined by the frequency of quality nonconformities and construction time on site; ti,mean is the ideal construction duration for procedure i; Qi,max is the optimal construction quality level, defined as the quality achieved when construction is completed within the ideal time and unaffected by factors such as geological conditions. When the duration is shorter than ti,min, fast-tracking may lead to quality risks; when it exceeds ti,max, repeated rework may occur on site, resulting in suboptimal quality.

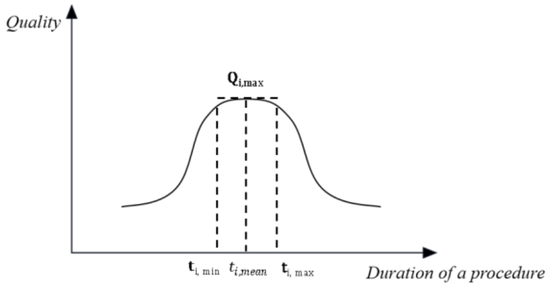


Figure 2. *Function of quality and duration of procedure i*

2.5 Tunnel Construction Safety-Schedule-Cost-Quality Correlation Model

In summary, this study focuses on safety management and establishes analytical models for safety, schedule, cost, and quality. Based on the concept of multi-objective optimization, the integrated model is formulated as follows.

$$\begin{cases} T = T_N + T_E \approx \sum_1^{N_P} \sum_{k=1}^{n_P} p_{P,k} * t_{P,k} + \sum_1^{N_E} \sum_1^{n_E} p_{E,k} * t_{E,k} + \sum_{i=1}^{n} T_{E,i} \\ T_{ES,i} = f(R_i) = \begin{cases} [0,1), & R_i = V \\ [1,3), & R_i = IV \\ [3,10), & R_i = III \\ [10,90), & R_i = II \\ [90,+\infty), & R_i = I \end{cases} \\ C = C_N + \sum_{l=1}^{L} \varphi_i (t_i - t_{n,i})^2 + \gamma T + \varphi(R_i) \cdot \left(\sum C_{Sg,i} + \sum C_{Sf,i} \right) \\ Q = avg\left(exp\left(-\frac{(t_i - t_{i,mean})^2}{m*(t_{i,max} - t_{i,min})^2}\right)\right) \\ S = g(R_i) = \begin{cases} 1, & R_i = V \\ 2, & R_i = IV \\ 3, & R_i = III \\ 4, & R_i = II \\ 5, & R_i = I \end{cases} \end{cases} \tag{13}$$

$$\textbf{s.t.} \begin{cases} t_{min,i} \le t_i \le t_{max,i} \\ T \le T_{max} \\ C \le C_{max} \\ S \le S_{max} \\ Q > Q_{min} \end{cases} \tag{14}$$

The Non-Dominated Sorting Genetic Algorithm III (NSGA-III) is a reference-point-based non-dominated sorting algorithm capable of generating a more uniformly distributed Pareto solution set using reference-point-based decision criteria. It is particularly suitable for solving high-dimensional optimization problems with more than three objectives, making it more useful for decision-makers in comparative analyses.

In the model developed in this study, there are a total of 29 decision variables: 10 excavation procedure durations ti for Grade III/IV surrounding rock, 10 excavation procedure durations tifor Grade V surrounding rock, 8 grouting procedure durations ti, and 1 safety risk index Ri.

There are 4 constraints:

(1) total construction duration must not exceed the upper limit of acceptable delay;

(2) total cost must not exceed the upper limit of investment;

(3) overall quality must not fall below 0.9;

(4) safety risk level must not exceed Grade II.

Considering the large number of variables, integer encoding is adopted in this study to reduce computational complexity and solving time.

3. CASE STUDY

The case project in this study is a subsea tunnel with a total length of 3768 meters. Due to the complex geological conditions of the tunnel project, both progress and various auxiliary measures—such as advanced geological forecasting, water exploration, and grouting for water sealing—must be carefully considered in this challenging construction environment. Achieving the above progress targets is therefore quite difficult. The relevant data and parameters regarding the construction processes of this project are presented in Table 1 and 2, wherein the estimated completion time for each process is derived from the construction organization design document.

Table 1. *Time Consumption of Excavation Processes*

Serial Number	Process Name	Planned Time per Cycle Advance (min)					
		Class III–IV			Class V		
		Most Probable	Min	Max	Most Probable	Min	Max
1	Scaling the tunnel face, moving to the working platform	40	30	50	40	30	50
2	Surveying and setting out, connecting air and water pipelines	30	25	35	30	25	35
3	Drilling	135	110	165	90	80	100
4	Charging and blasting	30	25	40	20	15	25
5	Ventilation and blast inspection	10	8	20	10	8	20
6	Mucking	165	140	195	150	120	170
7	Scaling	30	25	35	30	25	35
8	Installing steel frames and mesh	60	55	65	60	55	65
9	Installing rock bolts, foot locking bolts, and welding	30	25	38	30	25	38
10	Shotcreting	135	115	162.5	100	85	123
11	Cycle Time	665	558	805.5	560	468	661
12	In Total (h)	11.5	9.3	13.5	9	7.8	10.2

Table 2. *Time Consumption of Grouting Processes*

Serial Number	Process Name		Time Required (days)		
			Most Probable	Min	Max
1	5m Advance Grouting for Rock Consolidation	Drilling	2	1.8	2.5
2		Pipe Installation	0.5	0.4	0.6
3		Grouting	2	1.5	3
4	First Round Grouting	Drilling	2	1.8	2.5
5		Grouting	2.5	2	3
6	Second Round Grouting	Drilling	2	1.8	2.5
7		Grouting	2.5	2	3
8	Verification Drilling		1	0.5	1.3
9	In Total		14.5	11.8	18.4

The estimated completion times for the construction procedures are derived from the construction organization design documents. The functional relationships between construction duration and cost were obtained by reviewing relevant literature and integrating on-site project data.

In this study, the NSGA-III algorithm is implemented using the PYMOO library. PYMOO is a Python library specifically designed for multi-objective optimization and supports various evolutionary algorithms, including NSGA-II and NSGA-III.

Based on the model developed in this study, the number of reference points per dimension is preliminarily set between 10 and 18, the population size between 100 and 160, and the number of generations at 600. To determine the optimal reference point setting and population size, the hypervolume (HV) of the Pareto solution set obtained in the final iteration of each run is calculated. HV represents the volume enclosed by the Pareto front and the reference point; a larger hypervolume indicates a higher quality Pareto solution set.

After performing iterative computations with different combinations of reference points and population sizes, the results are shown in Table 3 and Table 4. The results indicate that for the characteristics of the model established in this study, setting the population size to 140, the number of reference points per dimension to 14, and the number of generations to 600 yields the optimal Pareto solution set.

Table 3. *Optimal Number of Reference Points*

Reference Points	10	14	18
Population Size	120	120	120
Number of Generations	600	600	600
HV	0.3840	0.4499	0.3883

Table 4. *Optimal Population Size*

Reference Points	14	14	14	14
Population Size	100	120	140	160
Number of Generations	600	600	600	600
HV	0.4317	0.4499	0.5033	0.4436

After computation, a total of 175 Pareto solutions were obtained and visualized, and Table 3 presents a subset of the optimal Pareto solutions..Among all the solutions:

(1) The maximum construction duration is 1695 days and the minimum is 1563 days. The required construction period is 57 months (i.e., 1720 days), achieving a maximum possible reduction of 132 days.

(2) The total cost ranges from a minimum of 597.17 million CNY to a maximum of 707.75 million CNY. Given that the project can accept a maximum cost of 800 million CNY, the model achieves an optimal cost reduction of 110.58 million CNY.

(3) The quality level ranges from a minimum of 0.9754 to a maximum of 0.9824, all above the minimum acceptable level of 0.9, thus meeting project requirements.

The safety risk level ranges from Grade V to a maximum of Grade II. Since the project does not accept Grade I risks, all solutions meet the safety requirements.

Table 5 presents a subset of the optimal Pareto solutions. In a Pareto solution set containing multiple non-dominated solutions, different stakeholders and decision-makers may prioritize the objectives differently.

When the current site condition is at Risk Level III and is about to escalate to Risk Level II, Solution 8 offers a construction duration of 1578.65 days, a total cost of 599.39 million CNY, and an overall quality level of 0.9810. If the goal is to downgrade the risk level with minimal additional time, Solution 1 may be selected, requiring 1608.22 days—an additional 29.57 days—while the cost rises to 620.80 million CNY, an increase of 22.41 million CNY.

Based on the procedure durations in each solution, decision-makers can reasonably prioritize objectives, adjust the model’s decision variables accordingly, and formulate practical emergency plans and safeguard measures—ultimately achieving optimal decision-making among safety, schedule, cost, and quality in tunnel construction.

Table 5. *Selected Pareto Solutions*

Solution ID	**Duration / d**	**Cost (million CNY)**	**Quality Level**	**Safety Risk Level**
1	1608.22	620.8	0.9796	II
2	1632.38	605.7	0.9815	II
3	1641.48	643.42	0.9784	II
4	1648.82	643.15	0.9783	II
5	1658.04	633.37	0.9791	II
6	1665.93	655.8	0.9779	II
7	1695.51	651.65	0.9780	II
8	1578.65	599.39	0.9810	III
9	1589.82	621.49	0.9790	III
10	1593.62	623.38	0.9789	III

4. CONCLUSION

This study proposes a multi-objective optimization model for safety, schedule, cost, and quality in subsea tunnel construction. The model is based on the actual duration ranges of various construction procedures and potential on-site safety risk levels, incorporating a total of 29 decision variables. It can be adapted to different projects by adjusting the variation ranges of these variables according to specific construction conditions. The model is solved using the NSGA-III algorithm.

Using a subsea tunnel project as a case study, site data were used to refine the variable ranges and define the upper limits for each objective. The optimized Pareto solution set was obtained through model computation. The results show that the construction schedule can be optimized by up to 132 days, and the cost by up to 110.58 million CNY, while both quality and safety levels remain within acceptable limits. These findings provide valuable support for decision-makers to develop effective construction strategies under varying project demands.

This study provides long-term and effective risk decision-making references for construction sites at the overall project level; however, the impact of safety risks on other risks is treated as a random variable within a fixed interval. In practical engineering, different types of safety risks lead to significantly varying losses in other risk categories. Therefore, it is necessary to refine risk classifications, investigate the correlations between individual risks and other risks during tunnel construction, translate safety risks into specific risk cases, and analyze the diverse consequences caused by different types of safety risks. Such an approach will provide construction stakeholders with more detailed and targeted risk decision-making sets.

5. ACKNOWLEDGMENTS

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