RESEARCH ON RISK MANAGEMENT OF SUBWAY TUNNEL CONSTRUCTION COMBINING CATASTROPHE THEORY AND LOW-CARBON BUILDING CONCEPTS

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Abstract. In this study, a multi-objective optimization framework is proposed by combining catastrophe theory with low-carbon building concept. By constructing a nonlinear model of energy consumption and security risk, the catastrophic characteristics of the relationship between low-carbon construction measures and risk level are discussed. Based on the actual construction data, this study evaluates the influence of key parameters on the construction process through simulation experiment and sensitivity analysis. An improved optimization algorithm is adopted to achieve a dynamic equilibrium between low-carbon goals and security risks.
Keywords: *subway tunnels, construction risk, energy consumption, risk level, multi-objective optimization*

Introduction

With the increasing global pressure to reduce carbon emissions, the construction industry, particularly subway tunnel projects, is required to reduce carbon emissions while ensuring construction safety. In recent years, global carbon reduction has become a central focus for governments and international organizations. According to the International Energy Agency (IEA), global carbon dioxide emissions reached 36.8 Gt (billion tons) in 2022, with the building and construction sector accounting for approximately 37% of total emissions and about 30% of global final energy consumption. The construction phase, particularly in underground projects, is characterized by high carbon emission due to the extensive use of energy-intensive machinery, construction materials, and energy consumption throughout the process. However, conflicts often arise between low-carbon construction measures and safety management. Efforts to reduce energy consumption and carbon emission may lead to increased safety risks, such as inadequate support strength or construction instability caused by accelerated tunneling speeds. Conversely, enhancing safety measures, such as excessive reinforcement redundant equipment use, can significantly increase energy consumption and carbon emission, contradicting the principles of sustainable development. Therefore, under the guidance of low-carbon building concepts, achieving a scientific and effective balance between energy consumption and safety in construction risk management has become a critical scientific challenge (Lederer et al., 2016; Wu et al., 2024).

To address these research gaps, this study proposes an innovative strategy based on a multi-objective optimization model that integrates energy consumption calculation, nonlinear risk analysis, and improved optimization algorithms. This approach

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comprehensively evaluates energy consumption, carbon emission, and safety risk levels during subway tunnel construction. The goal is to optimize construction management measures to minimize energy consumption and carbon emission while ensuring construction safety, thereby providing theoretical support and practical guidance for sustainable underground engineering practices.

Review of literature

Existing studies often focus on single-objective optimization, such as strategies aimed at minimizing energy consumption or maximizing safety. However, they tend to neglect the interdependent relationship between energy consumption and safety within a multi-objective optimization framework. In terms of energy consumption optimization, previous research primarily focuses on optimizing high-energy-consuming equipment, promoting low-carbon construction materials, improving construction processes, and implementing intelligent management systems. For example, to reduce the energy consumption of high-power equipment such as tunnel boring machines, researchers have proposed energy consumption control methods based on operational efficiency optimization, which are combined with new energy technologies and intelligent operational scheduling algorithms to minimize unnecessary power consumption while ensuring construction progress (Fan et al., 2022; Li et al., 2024; Zhang et al., 2024). Additionally, optimizing construction materials, such as promoting the use of low-carbon concrete, recycled steel and prefabricated components, has proven effective in reducing carbon emissions during the construction process (Liu et al., 2017; Li and Zhu, 2024). The adoption of modular construction techniques has demonstrated significant potential in reducing material transportation and optimizing construction workflows, thereby contributing to energy savings (Mao et al., 2021; Yuan et al., 2023). Meanwhile, the integration of information management techniques, such as IoT-based energy consumption monitoring systems, intelligent construction management platforms, and data-driven energy efficiency evaluation models, enables dynamic optimization of construction energy use, thereby enhancing the feasibility and intelligence level of low-carbon construction (Xue et al., 2015; Hanson et al., 2016).

Regarding risk management, researchers have developed various risk assessment methods to enhance the identification and prediction of construction safety hazards. Among these, risk assessment models based on the analytic hierarchy process, fuzzy comprehensive evaluation, and Bayesian networks have been widely applied for the quantitative analysis of construction safety risks (Zou and Li, 2010; Fang et al., 2011; Luo et al., 2024). These methods have significantly improved the accuracy and comprehensiveness of risk identification. Particularly in complex geological conditions and environments prone to sudden incidents, integrating numerical simulation and data-driven techniques into risk prediction models allows for the early warning of potential construction hazards (Wu et al., 2019; Zhang et al., 2021). For instance, researchers have used numerical simulations to analyze tunnel surrounding rock deformation, groundwater infiltration, and the stability of support systems to predict potential collapses and water seepage risks (Mu et al., 2014; Li et al., 2022). Additionally, Bayesian network models trained on historical data have been employed to achieve dynamic risk assessments of construction processes. However, current risk management research primarily focuses on the static assessment of individual risk types, lacking comprehensive analysis of the coupling effects among multiple risk factors. Specifically, the nonlinear evolution of risk

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behavior under the interaction of geological conditions, groundwater fluctuations, and construction process adjustments remains underexplored (Nikkhah et al., 2019; Liu et al., 2020). Furthermore, existing risk control measures are predominantly experience-driven. While they can reduce construction safety risks to a certain extent, they have not fully utilized data-driven intelligent analysis methods to achieve real-time and dynamic risk control (Saeedi et al., 2021; Xu et al., 2024).

Materials and methods

Analysis of construction energy consumption and carbon emission

Subway tunnel construction is a high-energy-consumption and high-carbon-emission underground engineering process that involves complex machinery, intensive energy use, and extensive material consumption, making the application of low-carbon building concepts particularly essential in this field. From energy consumption perspective, tunnel boring machines, concrete batching plants, and ventilation and drainage systems operate continuously, leading to significant energy consumption. Moreover, as construction sites are often located in urban centers with limited energy supply, optimizing energy use is crucial for cost reduction and sustainability improvement. From a carbon emissions perspective, the production of materials such as cement, steel reinforcement, and tunnel segments generates substantial carbon emissions, while the high durability requirements of tunnel support systems further increase material consumption. Therefore, optimizing material selection and utilization can effectively reduce construction-related carbon emissions and lower the carbon footprint over the entire lifecycle.

Calculation of construction energy consumption

In subway tunnel construction, energy consumption and carbon emission are critical indicators for evaluating low-carbon construction. The concept of low-carbon building emphasizes optimizing construction techniques and material usage to minimize energy consumption and reduce carbon emission, thereby mitigating negative environmental impacts. This section adopts a systematic analytical approach to quantify energy consumption and carbon emission during construction and explores optimization measures based on low-carbon building principles. The sources of energy consumption in subway tunnel construction primarily include operational energy consumption of construction equipment, energy consumption for material transportation, lighting system usage, and auxiliary facilities. A detailed analysis of each source is provided below.

The energy consumption of construction equipment E_c refers to the energy consumed by machinery such as tunnel boring machines, concrete mixers, and lifting equipment during construction. It can be expressed as:

$$E_c = \sum_{i=1}^{n} P_{c,i} \cdot t_{c,i} \qquad \text{(Eq.1)}$$

where $P_{c,i}$ represents the power of the i-th construction equipment (kW), indicating the maximum energy consumption capacity of the equipment per unit time; $t_{c,i}$ is the operating time of the i-th equipment(h), representing the total duration the equipment operates during the construction process; and n is the total number of construction equipment. If the shield machine power $P_{c,1}$=2500 kW, the shield machine operating time

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$t_{c,1}$=10 h, the concrete mixer power $P_{c,2}$=500 kW, the concrete mixer operating time $t_{c,2}$=6 h, and the total number of equipment n=2, then the total energy consumption of the shield machine and the concrete mixer in one day is: E_c=(2500×10)+(500×6)=25000+3000=28000 kWh.

The energy consumption for material transportation E_t refers to the energy consumed by transportation vehicles used on the construction site. It is calculated as:

$$E_t = \sum_{j=1}^{m} W_j \cdot d_j \cdot \varepsilon_j \tag{Eq.2}$$

where W_j is the weight of the j-th batch of materials (t), representing the total weight of the transported materials in that batch, typically including cement, steel reinforcement, tunnel segments, and other construction materials; d_j is the transportation distance (km), indicating the distance the batch of materials is transported from the starting point (such as a material supplier or warehouse) to the construction site; ε_j is the energy consumption coefficient of the transport vehicle (kWh/t·km), representing the amount of energy consumed per unit mass (1 ton) of material transported over a unit distance; m is the total number of transportation batches. If the concrete mass W_j=40 t, the transportation distance d_1=15 km, the energy consumption coefficient of the diesel truckε_1=0.35 kWh/t·km, and the number of transportation batches m=1, then the energy consumption for transporting one batch of concrete is: E_t=40×15×0.35=210 kWh.

The energy consumption of the lighting system E_l is determined by the total power of the lighting equipment and the duration of its operation. The calculation is as follows:

$$E_l = P_l \cdot t_l \tag{Eq.3}$$

where P_l represents the total power of the lighting system (kW), representing the total rated power of all lighting fixtures at the construction site; t_l denotes the operating time (h), indicating the total duration the lighting system remains operational during the construction period, which is generally influenced by construction scheduling and ambient lighting conditions. If the lighting system power P_l=100 kW and the lighting time t_l=12 h, then the daily energy consumption of the lighting system is: E_l=100×12=1200 kWh.

The energy consumption of auxiliary facilities E_a includes the energy used by ventilation systems, pumps, drainage systems, and other auxiliary facilities. It is calculated as:

$$E_a = \sum_{k=1}^{q} P_{a,k} \cdot t_{a,k} \tag{Eq.4}$$

where $P_{a,k}$ is the power of the k-th auxiliary facility (kW), representing the rated energy consumption of the facility, such as the power rating of a drainage pump determining its pumping capacity; $t_{a,k}$ is its operating time (h), indicating the accumulated duration the facility operates during the construction process; q is the total number of auxiliary facilities, including all supporting equipment such as ventilation systems, drainage systems, and other infrastructure. If the ventilation system power $P_{a,1}$=200 kW, the

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ventilation system operating time $t_{a,1}$=20 h, the water pump power $P_{a,2}$=150 kW, the water pump operating time $t_{a,2}$=24 h, and the total number of auxiliary facilities q=2, then the total daily energy consumption of auxiliary facilities is: E_a=(200×20)+(150×24)=4000+3600=7600 kWh.

After quantifying each energy consumption source, the total energy consumption E_{total} can be expressed as:

$$E_{\text{total}} = E_c + E_t + E_l + E_a \tag{Eq.5}$$

This refined formula enables a more precise analysis of the contributions of each energy source to the total energy consumption, facilitating the development of targeted low-carbon optimization measures (*Figure 1*).

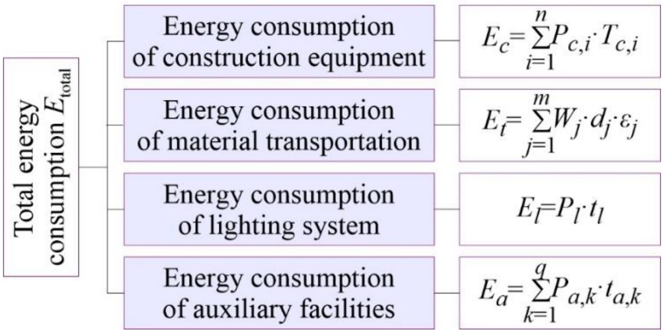

Figure 1. *Calculation of subway tunnel construction energy consumption*

Calculation of carbon emission

Based on energy consumption data, carbon emission during construction can be calculated. The total energy consumption E_{total} is composed of various energy types, such as electricity, diesel, and natural gas. If m types of energy are used during construction, the total energy consumption can be represented as the weighted sum of energy consumption by type:

$$E_{\text{total}} = \sum_{j=1}^{m} E_j \tag{Eq.6}$$

where E_j represents the energy consumption of the j-th energy type (kWh or L or m^3). To decompose E_{total} by energy type, it is necessary to understand the energy consumption characteristics of each construction phase and equipment. For example, some equipment may exclusively use electricity, while others rely on diesel or natural gas. The total consumption must be allocated to different energy types based on these characteristics.

The calculation of carbon emission employs the emission factor method, converting energy consumption data of different energy types into equivalent carbon dioxide emissions. The total carbon emission CO_2 can be expressed as:

$$CO_2 = \sum_{j=1}^{m} E_j \cdot \eta_j \tag{Eq.7}$$

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where η_j is the carbon emission factor of the j-th energy type ($kgCO_2/kWh$ or $kgCO_2/L$ or $kgCO_2/m^3$). The emission factors η_j are based on data standards published by the International Energy Agency (IEA) (*Table 1*). For different energy types, the emission factors should be adjusted according to their production methods and combustion characteristics. For instance, the carbon emission factor of electricity generated from fossil fuels is higher, while that of renewable energy is close to zero.

Table 1. *Emission factors of main energy types based on data standards published by the IEA*

Energy Source	**η_j/($kgCO_2$/unit)**
Diesel Fuel	2.68 $kgCO_2/L$
Gasoline	2.31 $kgCO_2/L$
Natural Gas	2.75 $kgCO_2/m^3$
Electricity	Varies by country and energy mix; refer to IEA's country-specific data

Low-carbon optimization measures

Based on the analysis of construction energy consumption and carbon emission, specific low-carbon optimization measures are proposed to effectively control energy consumption and carbon emission. By adopting a multi-objective optimization strategy, construction process improvements, equipment efficiency enhancements, and material management optimization are integrated. Specifically, the following measures can be implemented (*Table 2*):

Table 2. *Low-carbon optimization measures in subway tunnel construction*

Key measures	**Specific measures**
Process optimization	Device scheduling
	Peak load reduction
Equipment efficiency	High-efficiency devices
Material management	Optimized operations
	Low-carbon materials
	Waste reduction
	Recycled materials

First, rational scheduling of construction equipment operation can avoid simultaneous use of high-energy-consumption equipment, reducing peak loads. Second, selecting energy-efficient equipment and low-carbon construction materials can minimize material waste through process optimization. The selection of low-carbon materials should be based on their carbon footprint evaluation metrics, such as the carbon emission from steel production and the proportional use of concrete. In addition, the main drive system of the shield machine using variable frequency drive and the high-efficiency hydraulic pump station can reduce the energy consumption during standby and partial load conditions while maintaining the same rated output.

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Construction safety risk assessment and catastrophe theory analysis

Construction safety risk assessment

Construction safety risk assessment is a critical step in ensuring the safety and stability of subway tunnel construction. This study employs a systematic risk assessment model, integrating catastrophe theory for nonlinear analysis to investigate the evolution of safety risks during construction, particularly the abrupt changes in safety risks under variations in external environmental or construction conditions.

The Analytic Hierarchy Process (AHP) is used to classify potential risk factors in subway tunnel construction into three primary categories: construction environmental risks, equipment operational risks, and personnel behavioral risks (*Figure 2*). Construction environment risks primarily include adverse geological conditions (such as soil collapse and groundwater seepage), extreme weather events (like heavy rainfall and high temperatures), and the impact of surrounding structures. Heavy rainfall can rapidly raise the groundwater level, increasing the risk of water inrush in the tunnel; sustained high temperatures may adversely affect concrete curing quality and equipment heat dissipation, potentially triggering cascading safety risks. The quantification of these environmental factors is achieved using on-site monitoring data, such as earth pressure and groundwater level changes, combined with expert scoring to calculate the risk level of each factor. The expert scoring method is employed by engaging experienced industry experts to evaluate key risk factors, including the construction environment, equipment operation, and personnel behavior. Experts use a 1-9 grading scale to assess the importance, occurrence probability, and severity of risk factors, and the AHP is applied to calculate the weight of each factor. Finally, the overall risk level is determined using a weighted averaging method, integrating on-site monitoring data with expert evaluations to enhance the scientific rigor and applicability of risk assessment.

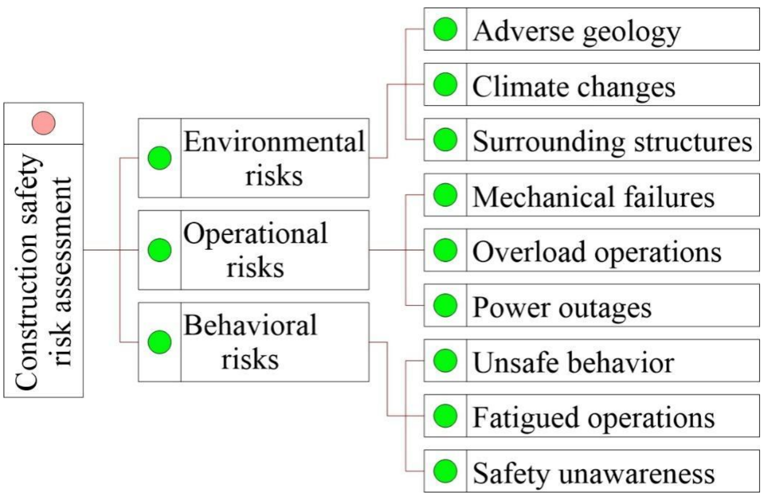

Figure 2. *Hierarchical structure for safety risk assessment in subway tunnel construction*

$$R_i = \alpha_i M_i + \beta_i \sum_{j=1}^{n} \omega_i S_{ij} \qquad \text{(Eq.8)}$$

where R_i represents the overall risk level of the i-th factor; M_i is the quantitative risk metric derived from monitoring data; S_{ij} is the score assigned by the j-th expert for the i-th factor; w_j is the weight of the j-th expert; α_i and β_i are coefficients adjusting the weights of monitoring data and expert assessments.

Equipment operational risks involve mechanical failures, overload operations, or power outages of construction machinery. These risks are assessed through an analysis of equipment maintenance records and operational data.

Personnel behavioral risks pertain to unsafe worker behavior, fatigue, and a lack of safety awareness. These risks are evaluated using historical accident data, behavioral observations, and surveys. The Fault Tree Analysis (FTA) method is employed to determine the probability and impact of behavioral risks, thereby calculating the overall risk level of personnel behavior.

The three categories of risks are integrated using AHP to compute the weights w_i of each risk factor, ultimately deriving the overall construction safety risk coefficient S_r:

$$S_r = \sum_{i=1}^{n} \omega_i \cdot R_i \tag{Eq.9}$$

where R_i is the risk level of the i-th factor; w_i is its weight. This method combines subjective judgments with objective data, enhancing the scientific validity and practicality of risk assessment.

Nonlinear analysis of construction safety risks

Following the risk assessment, a nonlinear analysis of construction safety risks is conducted. Subway tunnel construction involves complex environments where risk factors interact nonlinearly, exhibiting abrupt behavior under changes in external conditions or management measures (Qiao et al., 2021).

Key parameters are first selected and defined. Rock mass strength σ, groundwater level h, and tunneling machine pressure p are identified as major risk control factors based on their significant influence on construction stability and safety. The rock mass strength σ is a fundamental geological parameter that influences tunnel stability. During construction, the surrounding rock may undergo deformation or even instability due to stress redistribution, excavation-induced disturbances, and groundwater erosion. When the rock mass strength is low, its load-bearing capacity decreases, making it more susceptible to collapse or large deformations. The quantification of rock mass strength typically relies on uniaxial compressive strength, rock mass quality indices, and geo-mechanical classifications, which serve as key indicators for assessing the stability of the surrounding rock and its impact on construction safety.

The groundwater level h is a critical environmental factor affecting tunnel construction stability. In water-rich strata, groundwater pressure may lead to permeability failure of rock formations, rheological effects in weak surrounding rock, and water inflow risks for shield tunneling machines. A high groundwater level can cause sudden water inflow or leakage within the rock strata, posing severe threats to construction safety. Additionally, elevated groundwater levels increase shield machine propulsion resistance, leading to higher energy consumption.

The tunneling pressure p, as a controllable variable, directly determines the operational state of the shield machine during construction. The setting of tunneling pressure must

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comprehensively consider the soil pressure in the forward formation, groundwater infiltration pressure, and the load-bearing capacity of the support system. If the tunneling pressure is excessively high, the soil ahead may become overloaded, causing face heaving or blowouts. Conversely, if the tunneling pressure is too low, soil collapse may occur, forming voids that endanger construction safety. Therefore, the tunneling pressure p should be dynamically adjusted based on the geological conditions of the construction area to ensure the stable advancement of the shield machine.

A system potential function is then constructed to describe the relationship between construction safety risk levels and external control parameters. The system state variable x is the construction safety risk level, reflecting the system's risk state under different external conditions. The external control parameter λ denotes factors influencing risk levels, such as changes in construction environment or the intensity of low-carbon construction measures. The system potential function $V(x, \lambda)$ captures the system's stability and potential for abrupt changes. This study employs a polynomial form of the potential function, simple but effective for describing catastrophes:

$$V\left(x\right)=ax^2+bx^4-\lambda x \quad \text{(Eq.10)}$$

where x is the construction safety risk level; λ represents external environmental or construction management control factors; parameter a reflects the intrinsic stability of the system, mainly influenced by the surrounding rock strength; parameter b controls the nonlinear variation of the system at different risk levels and is related to external environmental factors.

The equilibrium points x of the system are obtained by solving the condition $\partial V/\partial x=0$:

$$\frac{\partial V}{\partial x}=3a\left(\lambda\right)x^2+2b\left(\lambda\right)x+c\left(\lambda\right)=0 \quad \text{(Eq.11)}$$

This equation describes the trajectory of equilibrium points as the control parameter λ. The stability of these equilibrium points is determined by analyzing the second derivative $\partial^2V/\partial x^2$: if $\partial^2V/\partial x^2>0$, the system is in a stable state; if $\partial^2V/\partial x^2<0$, the system is in an unstable state.

By varying the external control parameter λ, the system state variable x may exhibit catastrophic behavior. When λ reaches a critical value, the system can jump from one stable state to another, displaying a typical catastrophe. This behavior is visualized using potential function plots, where changes in the shape of the potential energy curve correspond to shifts in system stability (*Figure 3*).

To further investigate the dynamic evolution of risk catastrophes, bifurcation theory is applied to analyze how safety risks change with external parameters. Bifurcation diagrams illustrate the trajectories of risk level x as external parameter λ vary (*Figure 4*). For instance, under low-carbon construction measures such as reducing equipment operation or optimizing energy allocation, construction environment parameter λ change gradually, yet safety risk levels x may experience abrupt transitions from stable states to sudden changes, reflecting underlying safety hazards and nonlinear evolution characteristics.

Finally, the fuzzy set approach is introduced to analyze the sensitivity and vulnerability of construction safety risks. Different risk factors are integrated into a unified nonlinear framework to study their response to external disturbances. For example, the relationship

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between the risk level S_r and the intensity of low-carbon construction measures λ is modeled as a nonlinear function:

$$S_r = k_1\lambda + k_2\lambda^2 \quad \text{(Eq.12)}$$

where k_1 and k_2 are sensitivity coefficients reflecting the dependency of safety risks on low-carbon measures. Numerical simulations are conducted to analyze risk variations under different scenarios, identify critical control parameters, and develop corresponding risk mitigation strategies.

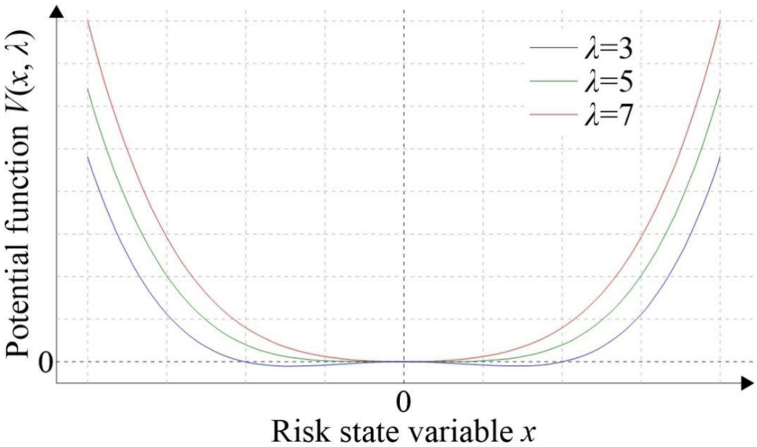

Figure 3. *Potential function V(x, λ) diagram changing with control parameter λ*

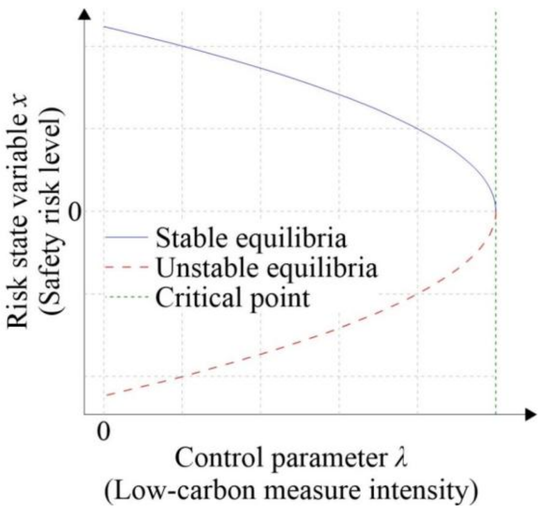

Figure 4. *Bifurcation diagram for subway tunnel construction safety risks*

Construction of a multi-objective optimization framework

Definition of objective functions

To achieve a balance between low-carbon emission and safety in subway tunnel construction, this study proposes a multi-objective optimization framework aimed at

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minimizing carbon emission and construction safety risks by optimizing construction strategies. The framework comprehensively considers energy consumption, carbon emission, equipment operational risks, and environmental impacts during construction. Based on nonlinear programming theory, the multi-objective optimization problem is transformed into a solvable mathematical form.

The framework defines two conflicting objectives: minimizing construction energy consumption and minimizing safety risks. Let the decision variables be y=(y1, y2, …, yn), where each yi represents a control parameter in the construction process, such as equipment operating time, material selection, or construction sequence. To express the low-carbon objective, the carbon emission function $f_1(y)$ is defined as:

$$f_1(y) = \alpha_1 \sum_{i=1}^{n} E_i(y) \cdot \eta_i \quad \text{(Eq.13)}$$

where $E_i(y)$ represents the energy consumption of the i-th control parameter (kWh); η_i is the corresponding carbon emission factor ($kgCO_2/kWh$); α_1 is a weight coefficient adjusting the importance of carbon emission in the overall optimization. The weight of the carbon emission objective α_1 is determined based on policy regulations, energy structure, technological feasibility, and the impact on the construction life cycle. In regions with strict carbon reduction policies, high fossil fuel dependency, and feasible low-carbon technologies, the weight should be increased.

Next, the safety risk minimization objective function $f_2(y)$ is defined as:

$$f_2(y) = \beta_1 S_r(y) + \beta_2 S_w(y) + \beta_3 A_e(y) \quad \text{(Eq.14)}$$

where Sr(y) denotes the construction safety risk evaluation coefficient; Sw(y) is the worker safety coefficient; Ae(y) represents emergency response capability for accidents; β_1, β_2, β_3 are weight coefficients evaluating the impact of these risk factors on overall safety. The safety risk weights β_1, β_2, β_3 are set according to construction complexity, accident statistics, worker safety management, and emergency response capacity. More complex environments, higher accident rates, and weaker emergency preparedness necessitate higher safety weights. The overall weight allocation is determined using the AHP or the Delphi method to optimize carbon emissions while ensuring safety, feasibility, and cost-effectiveness.

The two objective functions are combined into a multi-objective optimization problem:

$$\min\{f_1(y), f_2(y)\} \quad \text{(Eq.15)}$$

where $f_1(y)$ and $f_2(y)$ are mutually constrained objectives. Low-carbon construction measures may increase safety risks, while improving safety may lead to higher energy consumption and carbon emission.

Solution of multi-objective optimization problem

To solve the proposed multi-objective optimization problem and achieve coordinated optimization of carbon emission and safety risks under construction resource and technical constraints, this study designs a solution method based on an improved Genetic Algorithm (GA) (McManus, 2024). This method leverages GA's global search capability

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for complex optimization problems while incorporating adaptive strategies and elitism to enhance efficiency and solution diversity. The selection of GA is primarily based on its advantages in global search capability, diversity maintenance, and adaptability to complex constraint environments. Compared to traditional gradient descent and linear programming methods, GA does not require the objective function to be continuous or differentiable, making it more suitable for handling nonlinear, discrete, or complex constraint-based construction optimization problems. Additionally, GA simulates the natural evolution process by incorporating selection, crossover, and mutation mechanisms, effectively avoiding local optima and improving the quality of globally optimal solutions. Compared with Particle Swarm Optimization (PSO) and Simulated Annealing (SA), GA performs better in high-dimensional search spaces, maintains solution diversity through population evolution, and efficiently obtains a set of non-dominated solutions in multi-objective optimization using the Pareto front update mechanism, making it more suitable for balancing carbon emissions and construction safety risk optimization. The solution process involves several key steps, including population initialization, fitness evaluation, Pareto frontier construction, and evolutionary operations (*Figure 5*).

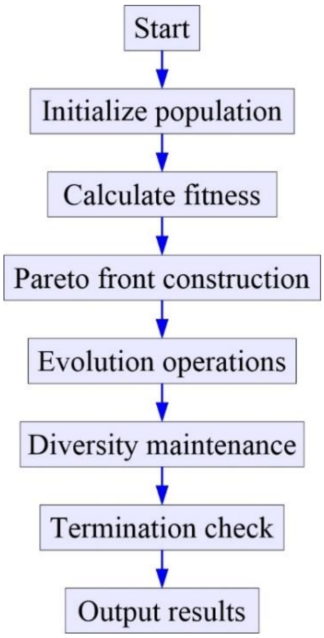

Figure 5. *Flowchart for the solution of the multi-objective optimization problem*

(1) Population initialization

The initial population is generated using the Latin Hypercube Sampling (LHS) method in the decision variable space. Assuming a population size of N, each individual y in the population represents a construction plan, i.e., a set of decision variables y=(y1, y2, …, yn). LHS ensures a uniform distribution of the initial population across the decision space, improving search efficiency and covering a diverse solution space.

(2) Fitness evaluation

For each individual y in the population, its corresponding objective function values, namely the carbon emission objective f1(y) and the safety risk objective f2(y), are computed using *formula (12) and (13)*.

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(3) Pareto frontier construction

In multi-objective optimization, Pareto optimal solutions are those that cannot improve one objective without deteriorating the other. The Pareto dominance relationship is used to compare individuals in the population: if solution y1 is no worse than solution y2 in all objectives and strictly better in at least one objective, y1 is said to dominate y2. A set of non-dominated solutions forms the Pareto frontier for the current generation. The Pareto frontier is iteratively updated to maintain a set of optimal trade-off solutions between low-carbon and safety objectives (*Figure 6*).

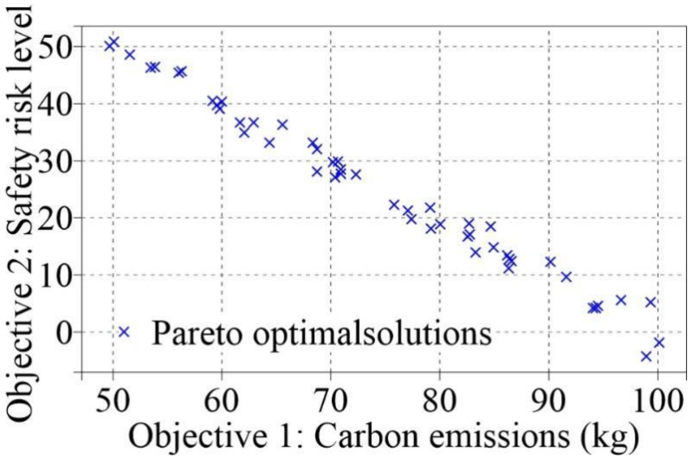

Figure 6. *Illustration of Pareto front solutions*

(4) Evolutionary operations

GA evolves the population through selection, crossover, and mutation operations:

Selection: Individuals with higher fitness are selected from the current population using fitness-based strategies such as roulette wheel selection or tournament selection. To enhance efficiency, an elitism strategy is employed to retain the top-performing individuals in the next generation, ensuring that high-quality solutions are not lost during evolution.

Crossover: Selected individuals undergo crossover operations with a probability pc to generate new offspring. Methods such as two-point crossover or uniform crossover are used to exchange information between parent solutions, enriching population diversity.

Mutation: Mutation operations are applied with a probability pm to randomly alter certain decision variable values, preventing premature convergence to local optima. An adaptive mutation strategy is adopted, where the mutation rate decreases as the number of generations increases, allowing for broad exploration in early stages and fine-tuned search in later stages.

(5) Crowding distance calculation and diversity maintenance

To maintain the diversity of the Pareto frontier solutions, a crowding distance metric is used. After each generation, the crowding distance for each Pareto frontier solution is calculated to measure its sparsity in the objective space. Solutions with higher crowding distances are prioritized, preventing the Pareto frontier from clustering in specific regions and ensuring uniform coverage of the solution space.

(6) Termination conditions and result output

The iterative process of GA ends when predefined termination conditions are met, such as reaching a maximum number of generations or observing no significant changes in the

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Pareto frontier over several iterations. The algorithm outputs a set of Pareto optimal solutions representing trade-offs between low-carbon and safety objectives. By analyzing and comparing these solutions, the most suitable construction strategy can be selected and further refined based on specific project requirements.

Additionally, the model incorporates a set of constraints reflecting practical construction requirements, such as resource limitations, project timeline demands, and environmental impacts:

$$g_i(y) \leq 0, \ i = 1, 2, \ldots, u \quad \text{(Eq.16)}$$

$$h_j(y) = 0, \ j = 1, 2, \ldots, v \quad \text{(Eq.17)}$$

where gi(y) represents inequality constraints, including maximum energy consumption limits, carbon emission caps, and equipment safety operation standards, while hj(y) represents equality constraints, such as resource balance and synchronization of key construction milestones. u and v denote the total number of inequality and equality constraints, respectively.

In summary, this proposed optimization framework simultaneously considers multiple interdependent objectives, whereas traditional methods typically focus on a single objective, overlooking the complex interactions among different factors. Based on nonlinear optimization theory, this method integrates catastrophe theory to model the nonlinear variations in construction safety risks and introduces potential function analysis and bifurcation theory to identify critical points and enhance risk prediction capabilities. For computational efficiency, an improved GA is employed, incorporating adaptive mutation strategies and an elite retention mechanism to accelerate convergence and prevent local optima. Furthermore, using Pareto front analysis, the framework provides a set of optimized solutions with different trade-offs, enabling decision-makers to select the most suitable optimization strategy based on specific construction requirements.

Results

Experimental design

To validate the effectiveness and robustness of the proposed multi-objective optimization model and assess the impact of low-carbon measures on construction safety risks, a simulation experiment was designed based on data from an actual subway tunnel construction project. The input data used in this experiment, such as mechanical power, operating time, and the number of equipment, are all derived from the construction logs, equipment manuals, and on-site monitoring records of the subway tunnel project, ensuring the representativeness of the data in engineering.

The experiment employs the MATLAB simulation platform combined with COMSOL Multiphysics for multi-physics coupling simulation, enabling energy consumption and risk evaluation in the construction process. The data originates from the Wuhan Metro Line 8 Phase III Yangtze River Tunnel Project. The project mainly traverses soft clay, fine sand layers, and local confined aquifers. The shield tunneling depth ranges from 15 to 25 meters. The construction environment is complex, involving multiple existing building pile foundations and underground pipelines along the route. It adopts the shield tunneling method and passes through complex geological conditions, including soft soil

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layers, sand layers, and water-rich strata. The construction process involves multiple challenges, such as the operation of high-energy-consuming equipment, carbon emission control, groundwater infiltration, and surrounding rock stability, making this project a representative case study. The experimental data are sourced from the on-site monitoring system, construction logs, equipment operation records, and environmental parameter monitoring data, covering multiple dimensions, including shield machine operating conditions, energy consumption, ground deformation, groundwater level variations, and the stress conditions of the support structures.

The experiment is divided into two main stages: simulation and sensitivity analysis. During the simulation stage, energy consumption and risk assessment models are constructed using the project data. The energy consumption formula for construction equipment is implemented in MATLAB, and total energy consumption Etotal and carbon emission CO_2 are calculated under different low-carbon strategies using *formula (4) and (6)*.

Construction safety risk levels are simulated using a nonlinear model based on catastrophe theory. In COMSOL Multiphysics, the impact of low-carbon measures on construction safety risks is simulated, including sudden risks caused by geological changes, equipment failure probabilities, and worker error sensitivity. The simulation incrementally increases the intensity of low-carbon measures, recording changes in the system risk state variable x to observe the emergence of catastrophic behavior and critical points. The stability of risk levels under various parameter conditions is analyzed using the potential *function (9)* from catastrophe theory.

The sensitivity analysis investigates how variations in key parameters affect the stability of the construction process. The core variables include the power parameter Pc,i in the energy consumption model, the control parameter λ in the safety risk model, and the rock strength σ, which is determined through drilling sampling and indoor triaxial testing. The groundwater level h is monitored in real-time using an automatic water level gauge. The tunnel boring machine pressure p data is directly obtained from the shield PLC control system. The Morris screening method, a global sensitivity analysis tool in MATLAB, systematically alters these parameters and records the construction system's responses. The goal of the sensitivity analysis is to identify which parameters significantly influence energy consumption and safety risks and analyze how parameter fluctuations alter system stability and catastrophic behavior.

Different optimization scenarios are as follows. Baseline scenario: No optimization measures applied. Optimization scenario 1 (equipment operation scheduling): Reduces total operating time of high-energy-consuming equipment by 10% and the number of active equipment by 20%; adjusts shield tunneling machine operation to off-peak hours and minimizes unnecessary generator usage. Optimization scenario 2 (material selection and usage): Replaces conventional concrete with recycled concrete and standard steel with low-carbon steel, reducing their respective carbon footprints by 15% and 10%; reduces material waste rate from 6% in the baseline to 3%. Optimization scenario 3 (construction process optimization): Adjusts shield tunneling speed from 5.5 m/h to 4.8 m/h and adopts sectional concrete pouring instead of integral pouring. Optimization scenario 4 (comprehensive optimization): Combines equipment scheduling, material selection, and process optimization for dynamic adjustment of operation, material usage, and construction processes.

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Evaluation of the effectiveness of low-carbon measures

As shown in *Figures 7-9*, equipment operation scheduling optimization (Scenario 1) reduces total energy consumption Etotal from the baseline value of 98573.34 kWh to 87391.26 kWh, a reduction of approximately 11.38%, while the construction safety risk coefficient Sr decreases from 7.84 to 7.72. This improvement is attributed to optimized operation schedules, which reduce the likelihood of equipment overload, thereby enhancing system stability. In contrast, material selection and usage optimization (Scenario 2), primarily through the substitution of low-carbon materials and the control of material waste, reduces carbon emission CO_2 from 24372.68 kg in the baseline to 20951.34 kg, a decrease of approximately 14.03%. However, as material optimization has limited direct impact on the construction process, its influence on safety risks is minimal, resulting in a slight increase in Sr from 7.84 to 7.89.

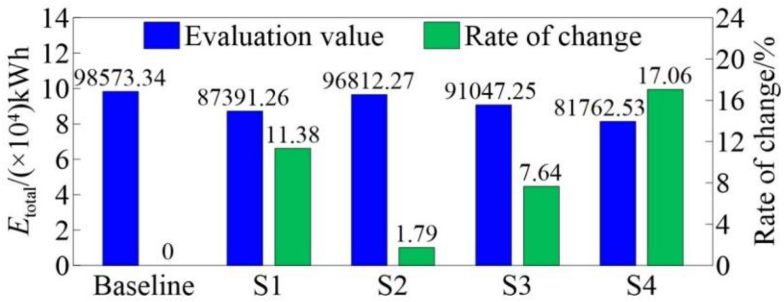

Figure 7. *Total energy consumptions of scenario 1-4 (S1-4) and their rates of change relative to baseline*

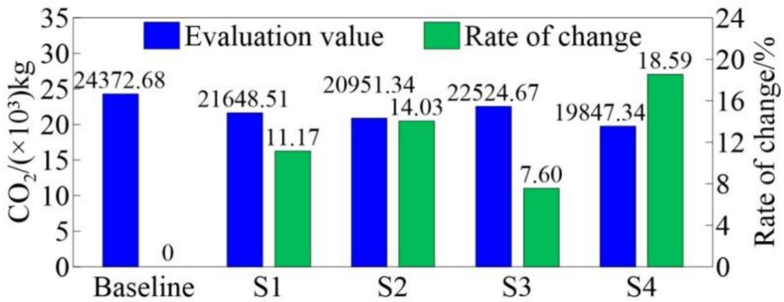

Figure 8. *Carbon emissions of scenario 1-4 (S1-4) and their rates of change relative to baseline*

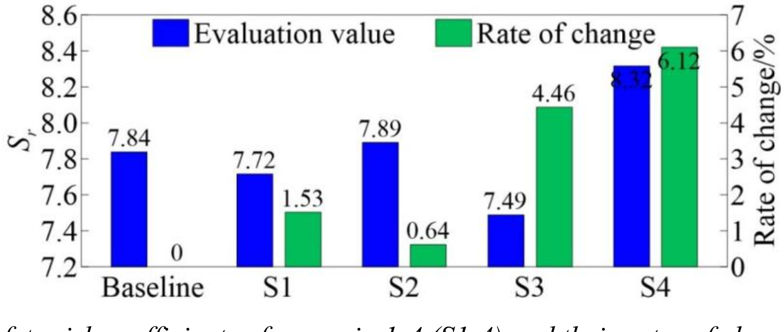

Figure 9. *Safety risk coefficients of scenario 1-4 (S1-4) and their rates of change relative to baseline*

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Construction process optimization (Scenario 3) further validates the impact of improved construction techniques on overall performance. By reducing the tunneling speed of the shield machine and adopting sectional pouring methods, Etotal decreases by 7.64%, and CO_2 are reduced by 7.60%. Simultaneously, process adjustments mitigate equipment peak loads and overload risks during construction, lowering Sr from 7.84 to 7.49, a reduction of 4.46%. These results indicate that optimizing construction processes can achieve low-carbon goals while providing some mitigation of safety risks.

Comprehensive optimization (Scenario 4), which integrates equipment scheduling, material optimization, and process improvement, achieves the greatest reductions in energy consumption and carbon emission, with Etotal decreasing by 17.06% and CO_2 by 18.59%. However, this scenario also results in a significant increase in construction safety risks, with Sr rising from the baseline value of 7.84 to 8.32, an increase of 6.12%. This is due to the compounded effects of multiple optimization measures, which increase the complexity of construction management. In particular, the synergistic implementation of equipment scheduling and material optimization may introduce uncertainties on-site, leading to elevated risk levels.

From the structural perspective of the model algorithm, these results reflect the inherent trade-offs of the multi-objective optimization model. Through the selection of Pareto optimal solutions, the model effectively identifies conflicts between low-carbon and safety objectives and explores different optimization pathways using the evolutionary mechanisms of the genetic algorithm. Sensitivity analysis of parameters such as equipment power, material carbon emission factors, and tunneling speed further confirms their critical role in implementing optimization measures. For instance, equipment power and carbon emission factors directly influence energy consumption and carbon emission, while adjustments to tunneling speed significantly affect the stability of system peak loads.

In summary, single optimization measures exhibit strong target orientation in reducing energy consumption or carbon emission while maintaining a controllable impact on safety risks. However, although comprehensive optimization achieves the best low-carbon outcomes, the cumulative effects of intensified optimization measures result in heightened construction risks, which cannot be overlooked. Therefore, in practical engineering applications, fine-grained trade-offs between low-carbon and safety objectives should be undertaken. Sensitivity analysis results should guide dynamic adjustments of key parameters to achieve optimal outcomes for multi-objective optimization.

Sensitivity analysis

First, as shown in *Figures 10-12*, equipment power Pc,i and carbon emission factor ηi have the most significant impacts on energy consumption and carbon emission, with sensitivity indices of 0.64 and 0.59, respectively. Equipment power, as the primary source of energy consumption during construction, directly determines the overall energy level. Optimizing equipment operation scheduling effectively reduces the proportion of simultaneous operation of equipment, thereby decreasing peak energy consumption and significantly reducing carbon emission. This is consistent with the experimental results. For example, optimization scenario 1 reduces Etotal by approximately 11.38% and CO_2 by 11.17% through scheduling optimization. Furthermore, the high sensitivity of the carbon emission factor ηi underscores the critical role of energy type selection in low-

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carbon building principles. The adoption of low-carbon energy sources can further amplify the emission reduction effects of energy consumption optimization.

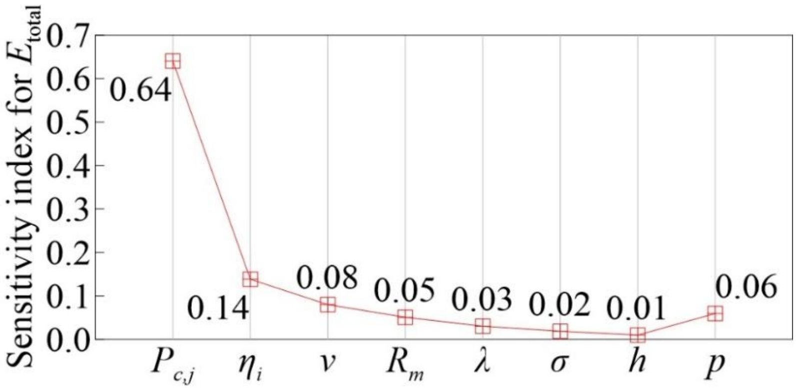

***Figure 10.** Sensitivity indices of key parameters for energy consumption*

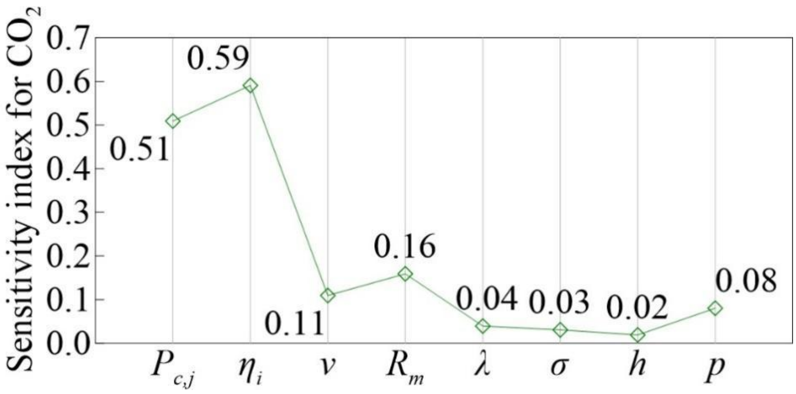

***Figure 11.** Sensitivity indices of key parameters for carbon emission*

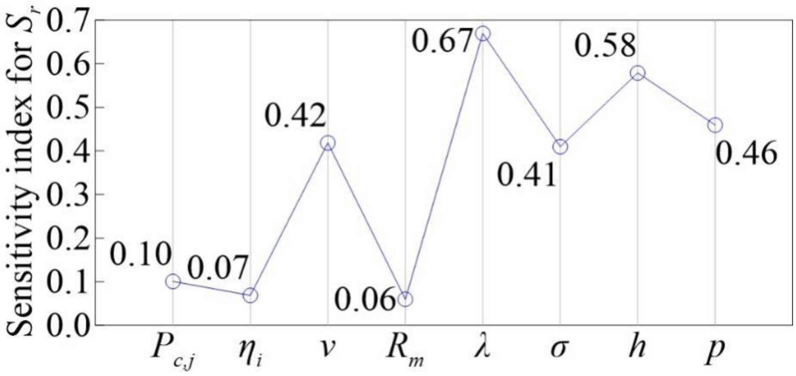

***Figure 12.** Sensitivity indices of key parameters for construction safety risks*

Tunneling speed v, tunneling machine pressure p, and rock mass strength σ exhibit high sensitivity to construction safety risks, their sensitivity indices are 0.42, 0.46, and 0.41, respectively. Adjustments in tunneling speed directly influence instantaneous loads and stability during construction, while tunneling machine pressure is crucial for

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balancing the rock mass and support systems. For example, experimental results show that reducing tunneling speed not only decreases energy consumption but also reduces Sr from 7.84 to 7.49, a reduction of 4.46%. Rock mass strength σ is closely related to geological conditions. Its lower sensitivity index indicates that under relatively stable construction environments, its influence is limited. However, when rock mass strength decreases significantly, it may trigger a nonlinear increase in safety risks, necessitating dynamic monitoring and adjustments to construction techniques in actual engineering projects.

Groundwater level h has a sensitivity index as high as 0.58, making it the most critical environmental parameter affecting construction safety risks. This result aligns closely with the characteristics of tunnel construction, where groundwater fluctuations may cause sudden leakage, water inrush, or shield machine jamming events. Under the control of the sudden risk parameter λ, the sensitivity index reaches 0.67, further emphasizing the importance of real-time risk monitoring and dynamic control. This indicates that even with the support of optimization measures, construction safety remains highly dependent on the collaboration between external environmental changes and on-site management practices.

The construction temperature T affects both material properties and equipment operational efficiency, with a sensitivity index of 0.38, indicating that high-temperature environments may increase the risk of equipment overheating, thereby affecting the stability of the tunneling machine. Additionally, variations in the hydration reaction rate of materials under different temperature conditions may impact concrete strength, indirectly influencing construction safety. The moisture content of construction materials M has a significant impact on energy consumption, with a sensitivity index of 0.35, suggesting that excessive moisture content may increase the energy required for concrete mixing while also affecting material strength and tunnel structural stability. The tunnel surrounding rock deformation D has a strong impact on construction safety risks, with a sensitivity index of 0.47, indicating that excessive rock deformation may lead to lining instability, increasing the likelihood of sudden accidents during construction.

From the perspective of the model algorithm, the sensitivity analysis results reflect the model's effective handling of complex multi-objective constraints. Through Pareto optimal solution selection and evolutionary search with the genetic algorithm, the model can balance the conflict between low-carbon and safety objectives while identifying the most influential parameters through sensitivity analysis. The high sensitivity of parameters such as equipment power, tunneling speed, and groundwater level highlights these variables as key control points in optimizing construction plans. Meanwhile, the adjustment of carbon emission factors and risk control parameters requires additional support at the engineering management level.

In conclusion, the sensitivity analysis clearly reveals the key driving factors for low-carbon optimization and safety risk control. Optimizing equipment power and carbon emission factors is the core pathway to reducing energy consumption and carbon emission, while the dynamic control of tunneling speed, tunneling machine pressure, and groundwater level is critical for ensuring construction safety. The model demonstrates strong robustness in overall optimization, providing theoretical support and practical guidance for integrating low-carbon building principles with risk management in subway tunnel construction.

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System risk status analysis

The experimental results demonstrate that construction safety risk levels exhibit significant nonlinear variation with increasing low-carbon measure intensity. When the low-carbon measure intensity λ<5.0, the system's risk state variable x increases slowly as the intensity grows. However, when λ>5.0 the risk level rises rapidly, with a sudden surge occurring between λ=7.0 and λ=9.0 (*Figure 13*). This indicates that a bifurcation phenomenon arises within this parameter range. To further analyze system stability, the first- and second-order derivatives of the potential function $V(x, \lambda)$ were computed. Near λ=7.0, solving $\partial V/\partial x$=0 revealed multiple equilibrium points. The second-order derivative analysis indicated the presence of unstable points (corresponding to $\partial^2 V/\partial x^2$<0), which are the critical regions where the system state undergoes bifurcation.

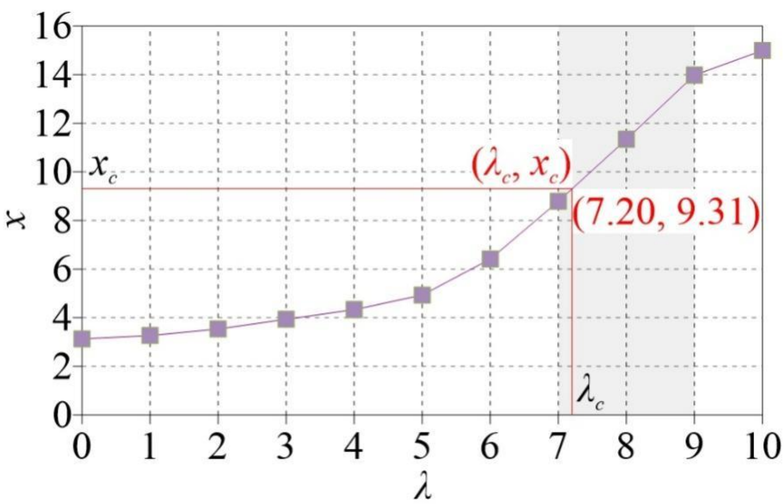

Figure 13. *Potential function curve for nonlinear analysis of system risk status*

The critical parameter values λ_c and the corresponding risk level x_c are approximately 7.2 and 9.31, respectively. Near the critical point, the risk level is highly sensitive to changes in the intensity of low-carbon measures. Even slight adjustments to the measures can trigger a transition from a low-risk state to a high-risk state. When $\lambda<\lambda_c$, the system exhibits a single stable state, with the risk level increasing gradually. As λ value approaches the critical value, the potential function transitions into a bi-stable structure, allowing the system to oscillate between low-risk and high-risk states. For $\lambda>\lambda_c$, the system completely enters a high-risk zone, characterized by a nonlinear explosion in the risk level.

The experimental results clearly demonstrate that construction safety risks exhibit bifurcation behavior when the low-carbon measure intensity reaches a certain threshold (critical point). As the intensity of low-carbon measures gradually increases, the system's risk level evolves nonlinearly from slow growth to rapid escalation. The potential function analysis further reveals the stability characteristics of the system state under varying parameter conditions and its critical point properties. These findings validate the applicability of bifurcation theory in construction risk analysis and emphasize the importance of dynamically regulating the intensity of low-carbon measures. Particularly near the critical point, more refined control strategies are required to prevent the system from entering a high-risk state.

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Although the simulation experiments in this study validate the effectiveness of the optimization model, certain limitations remain. First, the experimental data are based on a specific engineering case, and the generalization capability of the model requires further validation. Second, some parameters involve uncertainty, and the potential function parameters in catastrophe theory are constrained by data availability, which affects optimization accuracy. Additionally, the experiments do not fully account for the dynamic variations in the construction environment. Future studies could integrate real-time monitoring and adaptive optimization techniques to enhance the model's adaptability. Moreover, the actual implementation effectiveness of the optimization strategy is influenced by construction management factors, necessitating further research on the integration of optimization strategies with engineering management. Future research directions include expanding datasets, adopting intelligent parameter optimization, and incorporating IoT and BIM technologies to enable real-time monitoring and feedback control. Furthermore, exploring the application of multi-objective optimization in other underground engineering fields can improve the feasibility and engineering applicability of the proposed optimization approach.

Discussion

The multi-objective optimization framework proposed in this study is not only applicable to the low-carbon and safety management of current metro tunnel construction but also provides theoretical support and technical guidance for complex construction environments in future urban rail transit projects. In the development of underground transportation networks, challenges such as ultra-deep tunnels, high-stress environments, weak surrounding rock formations, and complex geological conditions will become more prominent. The integration of catastrophe theory with optimization models can be utilized to identify critical risk thresholds in advance, optimize construction parameters, and ensure construction safety. Meanwhile, with the advancement of carbon neutrality policies, low-carbon construction technologies will be more widely applied in smart rail transit projects, such as intelligent control-based shield tunneling energy optimization, large-scale adoption of recycled building materials, and real-time intelligent monitoring of construction processes. The proposed method can be extended to automated construction management systems, integrating the Internet of Things (IoT) and Digital Twin technology to dynamically optimize energy consumption and safety risks, enabling more efficient, sustainable, and intelligent urban rail transit development.

Conclusion

This study systematically explores the nonlinear coupling relationships among energy consumption, carbon emission, and safety risks in subway tunnel construction by integrating catastrophe theory and low-carbon building principles. A multi-objective optimization model is constructed to balance the conflict between low-carbon objectives and safety objectives. The results of simulation experiments and sensitivity analyses based on the optimization model indicate that equipment power, carbon emission factors, tunneling speed, groundwater level, and tunneling machine pressure are key parameters influencing construction energy consumption, carbon emission, and safety risks. Optimization of equipment power and the selection of low-carbon energy significantly reduce construction energy consumption and carbon emission, with maximum reductions

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of 17.06% and 18.59%, respectively. Meanwhile, adjustments to tunneling speed and dynamic control of groundwater levels have significant impacts on risk levels, with sensitivity indices of 0.42 and 0.58, respectively, highlighting that optimizing construction techniques and environmental monitoring are core pathways for risk management. These research findings not only provide scientific guidance for engineering practice, but also offer insights for policymakers to optimize building standards and formulate green building regulations, thereby achieving low-carbon construction under the premise of safety.

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