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Risk-based optimization of emergency response systems for accidental gas leakage in utility tunnels

Jitao Cai [a], Jiansong Wu [a,*], Shuaiqi Yuan [b], Genserik Reniers [b], Yiping Bai [a]

[a] School of Emergency Management and Safety Engineering, China University of Mining & Technology, Beijing 100083, China
[b] Safety and Security Science Group, Faculty of Technology, Policy and Management, TU Delft, Delft, the Netherlands

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ABSTRACT

Focusing on the effective configuration of emergency response systems in utility tunnels, this study proposes an innovative approach to optimize existing emergency response systems based on a consequence rapid prediction model and genetic algorithm. In the proposed approach, the interactions between different emergency response components are considered to perform a rapid gas dispersion prediction. Furthermore, the predicted gas concentration distribution is employed to estimate the quantitative explosion risks by combining the equivalent cloud method and the Baker-Strehlow model. Finally, the cumulative and cascading risk index are proposed and combined for systematic optimization by using a genetic algorithm. A case study is performed to demonstrate the feasibility of the proposed approach. The results indicate that the optimized emergency response systems effectively reduce both the cumulative and cascading risk level. This study provides technical support for emergency response system design and helps to improve the safety-risk-control capabilities of utility tunnels.

1. Introduction

The construction of utility tunnels has been promoted to meet the growing and urgent demand for sustainable city development, given its potential to facilitate energy supply and sustainable urban planning by housing and managing various municipal utilities in unified underground tunnels [1]. As one of the most threatening safety hazards in urban tunnels, the natural gas pipeline has attracted significant concerns due to the possibility of causing catastrophic consequences after gas leakage [2,3]. “Safety barrier” is a widely-used term to present all kinds of preventive measures and mitigation measures that are used to prevent the happening of undesired accidents or mitigate their corresponding consequences [4]. In terms of unexpected gas leakage in utility tunnels, emergency response systems play an important role and work as mitigative safety barriers to reduce the gas leakage consequences and prevent the happening of cascading events. Effective optimization of these emergency response systems helps manage accident risks in utility tunnels and improves emergency response efficiency. Therefore, the performance assessment and optimization of emergency response systems is an important research topic with practical significance for promoting the safe operation and risk control of utility tunnels.

According to the requirement of *Technical Specification for Urban Utility Tunnel Engineering (GB 50838-2015)* [5], emergency response systems for assuring the safety of natural gas compartments mainly include gas sensors, ventilation fans, and shut-down valves etc. Previous studies focused on the emergency response system optimization in utility tunnels based on experimental or numerical methods. Mi et al., [6] investigated the effectiveness of emergency ventilation and revealed that appropriate ventilation modes can create better evacuation conditions. An et al., [7] studied the effect of inclination angle and longitudinal ventilation on the temperature distribution. Li et al., [8] conducted a reduced-scale experiment with an analysis of the wind speed and pressure distribution to optimize the ventilation efficiency. Wang et al., [9] proposed a novel piston-wind ventilation strategy to improve the thermal environments and facilitate the safe operation of pipeline systems. The effectiveness of ventilation systems in diluting leaking gas was analyzed in terms of ventilation speeds [10,11,2]. Similarly, ventilation vent sizes [12] and ventilation mode design [13,14] were also investigated.

Moreover, the optimization of gas sensor layouts is attracting more and more attention considering its effectiveness in the timely detection and alarm in case of gas leakage scenarios. Wu et al. [2] investigated the number of gas sensors required in the natural gas compartment for achieving source term estimation of gas leakage based on data

* Corresponding author.
E-mail address: jiansongwu@hotmail.com (J. Wu).

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assimilation methods. Zhou et al., [15] conducted an optimization of gas sensor layouts considering their distribution at the cross-sections by using the CFD-adjoint-based method. With the introduction and investigation of the resilience of utility tunnels, Bai et al., [16] performed an optimization of sensor layouts and ventilation strategies based on numerical simulations. To determine appropriate strategies for safety barrier allocation, previous studies mainly compared the performance of each strategy by using numerical simulations. The implementation of a large number of numerical simulations is inevitably computationally expensive; Meanwhile, the interaction between different safety barriers should also be well addressed to achieve a comprehensive improvement of the emergency response systems, instead of focusing on individual safety barrier optimization separately; Furthermore, previous studies have focused on optimizing safety barriers based on specific physical parameters such as temperature and concentration. However, the safety state of the utility tunnel cannot be adequately measured by a single physical quantity.

To address aforementioned issues, worst-case scenarios are typically prioritized for numerical simulation analysis to reduce computational expense. And several index-based methods have been implemented in utility tunnels to evaluate the performance of safety barriers. Xu et al., [17] integrated Flame Acceleration Simulator (FLACS) with probability analysis to create an Exceedance frequency index. However, the possible intervention of various safety barriers was not fully considered. Bai et al., [16] conducted a study on the optimization of emergency strategies based on a proposed resilience assessment model. However, this study has some limitations in terms of modeling and evaluating the consequences of gas explosions. Most importantly, the search for the best configuration of safety barriers involves the solution of a combinatorial optimization problem, in which multiple choices of safety barriers are possible and accompanied by varying risk levels. This is a challenging issue because it is impractical to enumerate and evaluate every possible combination of safety barriers in practice.

Recent advancements in risk management and safety optimization across various engineering domains highlight the integration of optimization algorithms with traditional engineering principles. These studies include the development of multi-objective optimization model for gas detector placement [18,19], robust multi-objective optimization for safety barrier performance in NaTech scenarios [20], and cost-effective models for chemical risk reduction [21–23]. Additionally, mixed-integer linear programming for system resilience, goal programming for firefighting strategies, and AI-driven robust optimization for tunnel construction demonstrate the trend towards more efficient, reliable solutions [24–26]. The introduction of the buffered optimization and reliability method (BORM) further exemplifies progress in tackling complex reliability-based optimization challenges in diverse engineering systems [27,28]. But up to now, a systematic approach for risk-based optimization of utility tunnel emergency response systems is still lacking, particularly considering gas leakage and explosion scenarios. Targeting this gap, this study integrates a rapid consequence prediction model that considers interacting safety barriers, risk constraints, and the genetic algorithm within an optimization framework. This approach enables safety barriers to mitigate the magnitude of risk to the greatest possible extent and prevent the occurrence of cascading events in other compartments of utility tunnels.

Regarding the methodological innovations and the relevance to the field of the safety of critical infrastructures, the main contributions of this study are concluded as follows:

This study developed a consequence rapid prediction model (CRPM) by integrating a gas dispersion model, equivalent cloud method, Baker-Strehlow model, and emergency response systems modeling. Compared with previous methods, it has significant advantages in assessing the entire accident evolution process (from gas leakages to explosions) while considering the intervention of emergency response systems. This methodological improvement allows a more comprehensive and reasonable/accurate consequence assessment, contributing to an appropriate safety risk assessment of utility tunnels. Furthermore, a risk-based optimization approach has been proposed using the CRPM model to optimize existing utility tunnel emergency response systems, offering an exploratory attempt and practical solution for the risk-based design and optimization of safety-critical systems. This study helps to enhance the risk-control capability of emergency response systems regarding the safety of utility tunnels and boosts the safety of complex technological systems. The developed method may also be applied to the safety risk control and risk-based optimization of other critical infrastructures.

The remainder of this study is organized as follows: In Section 2, the methodology for developing the risk-based optimization approach is presented. Furthermore, an illustrative case study in a typical utility tunnel scenario is presented in Section 3 to demonstrate the application of the proposed approach. Finally, Section 4 presents the concluding remarks of this study.

2. Methodology

This section presents an overall framework of the proposed approach first. The following Sections provide detailed explanations of the three steps involved in this approach.

2.1. Overall framework

The framework of the proposed approach is presented in Fig. 1. To model the evolution of the accident scenarios, we begin with identifying potential accident scenarios with the consideration of the intervention of safety barriers after gas leakage. After that, risk modeling should be conducted, in which the probability analysis and consequence analysis should be performed. Finally, the obtained risk indexes are used to configure the optimization functions, and thereby the optimization algorithm can be implemented to identify an optimal strategy for the emergency response system allocation and reconfiguration.

2.2. Accidents scenario building

Fig. 2 demonstrates the possible accident scenarios and their evolution paths within the natural gas compartment. The accident evolution process can be divided into three main stages. Firstly, a catastrophic consequence begins with gas leakage. Subsequently, the flammable gas may disperse and accumulate in the compartment. If the accumulated gas was ignited, a gas explosion would happen. Finally, cascading events may occur if the overpressure exceeds the compressive strength of the concrete wall [29], which may induce damage to nearby compartments. It is assumed that emergency response systems, including combustible gas sensors, variable frequency fans, and gas pipeline shut-down valves, are allocated in a good manner to mitigate the consequences of gas leakage and prevent possible cascading events. To appropriately describe the accident evolution process and evaluate the corresponding consequences, the possible accident scenarios were identified with the consideration of the intervention of safety barriers on accident consequences.

2.2.1. Accident scenario identification

According to the evolution paths mentioned above, three main events of accident evolution are identified: (i) Gas leakage and dispersion; (ii) safety barrier interventions; (iii) Ignition and explosion. As a result, the possible scenarios associated with gas leakage events (i.e., initial events in the evolution paths) should be identified first. Typically, the leakage scenario set should be able to represent any possible leakage scenario to fully reflect the leakage and subsequent accident risk. The leakage scenario set is established by randomly combining the leakage source set (defined by leakage location, hole size, leakage direction, etc.) and the wind field set (defined by wind speed and direction). In this study, several main principles are proposed to reduce the scenarios to an acceptable level considering a balance between scenario integrity and

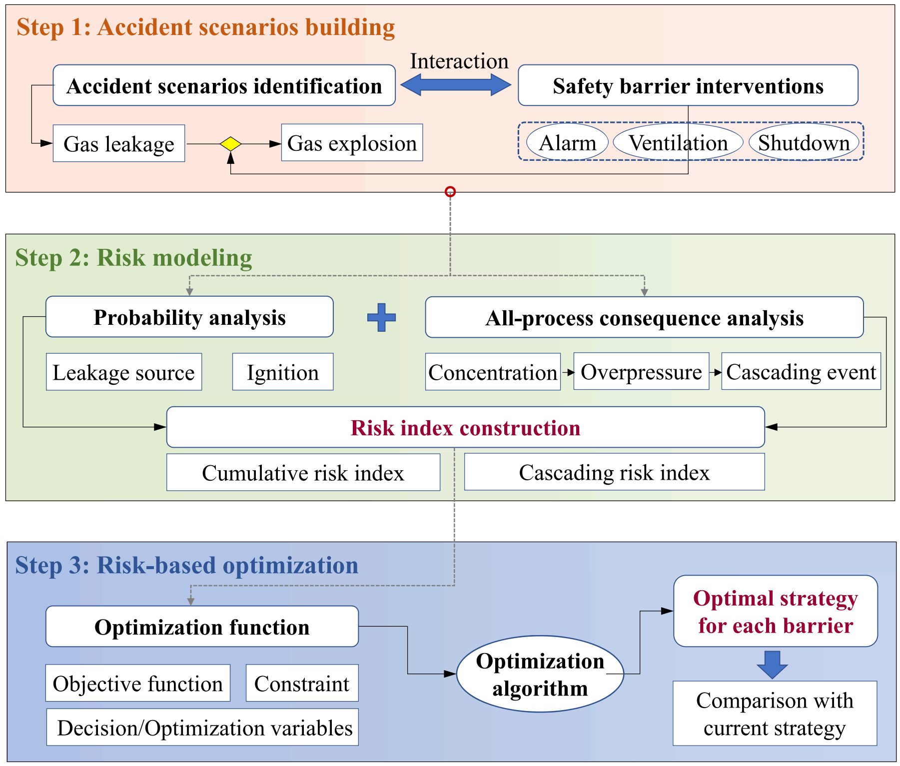

Fig. 1. The framework of the proposed approach.

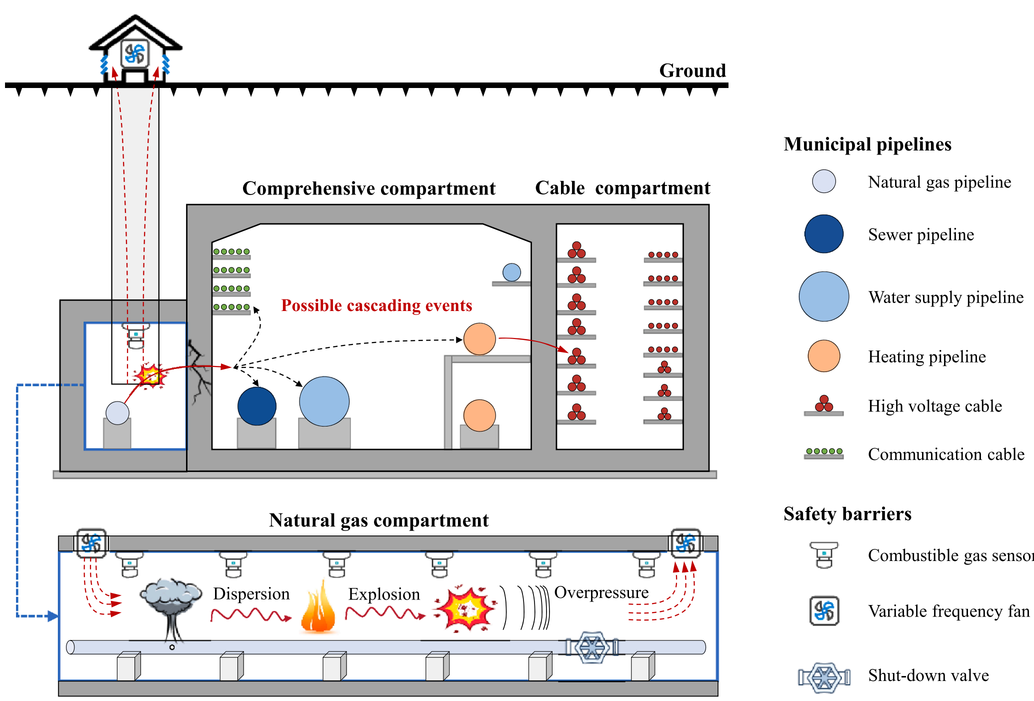

Fig. 2. Accident scenarios and corresponding evolution paths in utility tunnels.

computational costs. First, the uncertainty of the wind field is not considered because the natural gas compartment has a predetermined ventilation mode, resulting in a relatively steady wind field. Second, the leakage direction can be simplified and not involved in the leakage scenario set since it has a relatively small effect on the gas leakage and dispersion process. This assumption is reasonable because the natural gas compartment in utility tunnels is designed as a long and narrow structure. When a gas leakage occurs, the leaking gas quickly mixes within the cross-section and is transported along the length direction of the utility tunnel due to mechanical ventilation [16]. Therefore, the leakage location and hole size are regarded as uncertain factors in the construction of the leakage scenario set. According to the 11th gas pipeline incident report of the European Gas Pipeline Incident Data Group (EGIG), the leakage hole size can be divided into three categories [30]: (i) pinhole, the effective diameter of the hole is smaller than or equal to 2 mm; (ii) the effective diameter of the hole is larger than 2 mm and smaller than or equal to the diameter of the pipe (300 mm in this study); (iii) the effective diameter of the hole is larger than the pipeline diameter. Three representative hole sizes are selected to represent the three types of leakage hole sizes, namely, 20 mm for pinhole leakage, 150 mm for hole leakage, and 300 mm for rapture leakage [18]. With the consideration of the randomness of leakage locations, we formulated the gas leakage locations as a uniform distribution with distance intervals of 5 m. Finally, a total of 117 cases are generated and regarded as the leakage scenario set considering the uncertainties of leakage location and leakage hole size, as illustrated in Table 1.

2.2.2. Operation mode of emergency response systems

According to the regulation of *Technical Specification for Urban Utility Tunnel Engineering* (GB 50838–2015) [5], three primary components (i.e., gas sensors, ventilation fans, and shut-down valves) are accommodated as emergency response systems in the natural gas compartment to cope with unexpected gas leakage accidents. Fig. 3 shows the operation mode of the emergency response systems. When an undesired leakage accident happens, the gas sensors first detect the leak as soon as the gas concentration reaches 1 % VOL. Subsequently, both the ventilation fan and shut-down valve are activated to execute their respective emergency actions at a concentration of 1.25 % VOL. In such conditions, the ventilation rate will increase from 6 times/h, in a normal situation, to 12 times/h, in an emergency scenario. Moreover, the activation of the shut-down valve could cause a gradual pressure drop inside the natural gas pipeline and lead to a gradual leakage rate decrease. However, despite the safety barriers' efficacy, the optimal configuration remains challenging as the distribution of gas clouds and corresponding risks vary during the gas dispersion process. Taking a specific safety barrier as an example, a large ventilation rate helps to decrease gas concentration but also might be beneficial to the mix of leaking gas, which inevitably forms a large volume of the explosive gas cloud. And the interaction between various components of the emergency response system further exacerbates the problem's nonlinear features. Therefore, optimizing safety barriers is a nonlinear combinatorial problem that requires balancing the risk level, costs, and emergency decision-making. To address this issue, we propose defining a spatiotemporal risk-based index to represent these complex and interactive relations and use it for inverse optimization of safety barriers.

2.3. Risk modeling

In this section, probability analysis and consequence analysis are introduced to achieve the risk modeling of gas leakage scenarios. Two novel risk indexes (i.e., cumulative risk and cascading risk) are proposed to evaluate the effectiveness of emergency response systems considering the severity of gas accumulation and the probability of cascading events in multiple compartments.

2.3.1. Probability analysis

As mentioned in Section 2.2.1, the leakage scenario set mainly includes the uncertainty of leakage locations and hole sizes. With the consideration of a uniform distribution of the leakage location variable, it can be exempted from the probability calculation. When it comes to subsequent explosion of gas leakage accidents, the ignition probability should be involved. Therefore, we present the statistical data, obtained from the 11th gas pipeline incident report of the EGIG, in Table 2. And the specific scenario probability can be calculated by the Formula (1) as follows:

$$P_L(i) = P_{occur}(i) * P_{igni}(i) \tag{1}$$

Where

P_L is the occurrence probability of any gas leakage scenario belonging to the leakage scenario set L,

P_{occur} is the occurrence probability of the specific hole size,

P_{igni} is the ignition probability related to the specific hole size,

i is the number of leakage scenarios, ranging from 1 to $N_L = 117$.

Table 1

Leakage scenario set within the natural gas compartment.

No. of Leakage scenarios	Leakage location /m	Range of hole size /mm	Representative diameter/mm
1–39	[5, 10, 15, …, 190, 195]	Pinhole: 0–20	20
40–78	[5, 10, 15, …, 190, 195]	Hole: 20~300	150
79–117	[5, 10, 15, …, 190, 195]	Rapture: >300	300

2.3.2. Consequence analysis

A consequence rapid prediction model (CRPM) is developed to quantitatively describe the interaction between the accident evolution and the safety barriers in utility tunnels, as well as evaluate its corresponding consequences.

Firstly, based on the previous work [16], a one-dimensional gas dispersion model is discretized by the finite volume method (FVM) to account for the gas leakage and dispersion process in the natural gas compartment, which can be seen in the Formula (2).

$$\frac{\partial \rho c}{\partial t} + \frac{\partial(\rho u c)}{\partial x} = \frac{\partial}{\partial x}\left(D\frac{\partial c}{\partial x}\right) + S \tag{2}$$

Where

c represents the volume fraction of leaking natural gas (v/v),

ρ is the density of the leaking natural gas (kg/m^3),

u is the ventilation speed corresponding to the x-direction (m/s),

D is the gas diffusion coefficient (m^2/s),

S is the leakage source term (kg/(m^3·s)).

Furthermore, the effect of safety barriers is modeled by qualitatively introducing their "Output" behavior (Fig. 3) into the gas dispersion model. For combustible gas sensors, the gas concentration predicted by the gas dispersion model would be recorded at all times. When the alarm value is reached at any gas sensor, the subsequent safety barriers can be activated, specifically, 1.00 %VOL for the ventilation fan and 1.25 % VOL for the shut-down valve. Concerning the ventilation fan, the ventilation rate is transformed from 6 times/h to 12 times/h dynamically, which will be converted to ventilation speed in Formula (2) by Formula (3) shown as follows [31]:

$$u = \frac{n \times V}{3600 \times F} \tag{3}$$

Where

n is the ventilation rate (times/h),

F is the area of the ventilation vent (m^2),

V is the volume of the utility tunnel (m^3).

With regard to the effect of the shut-down valve, the drop in the pressure gradient between the natural gas pipeline and external space cause a dynamic variation of leakage rate in the location of the leakage hole, which can be calculated by the Formulas (4)–(6) as follows [16,4]:

$$Q_M = C \cdot A \cdot P_a \sqrt{\frac{k \cdot M}{R \cdot T}\left(\frac{2}{k+1}\right)^{\frac{k+1}{k-1}}} \tag{4}$$

$$Q_E = Q_M \cdot \exp\left(\frac{-Q_M}{m_0}(t - t_E)\right) \tag{5}$$

$$m_0 = A \cdot L_D \cdot \rho \tag{6}$$

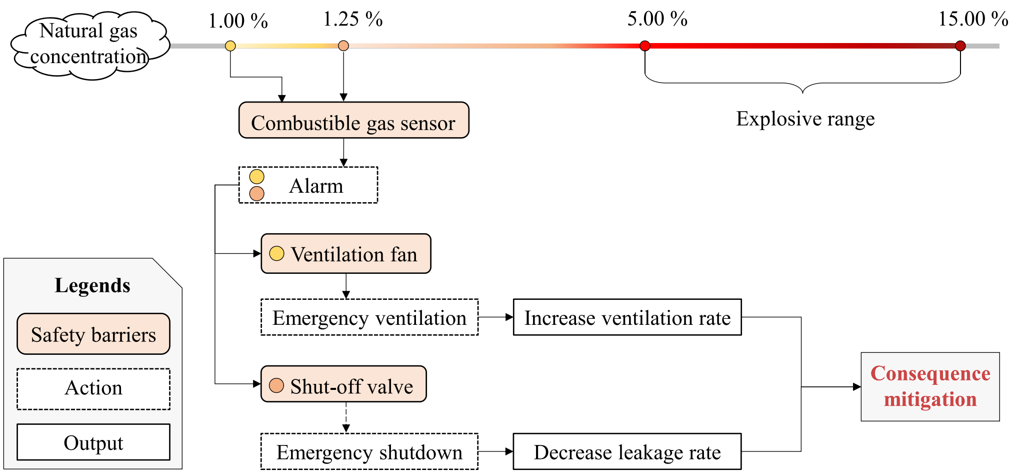

Fig. 3. The operation mode of emergency response systems in case of gas leakage accidents.

Table 2
Occurrence and ignition probability for different accident scenarios [30].

Range of hole size	Occurrence probability /1000 km·yr	Ignition probability /%
Pinhole	0.088	4.7
Hole	0.022	2.2
Rapture	0.013	4.7
Unknown	0.003	/

Where

Q_M is the initial leakage rate (kg/s),

C is the release coefficient, ranging from 0.9 to 0.98 based on the hole shape,

A is the area of the leakage hole (m^2),

P_a is the pressure of the natural gas pipeline (Mpa),

k is the isentropic index and is equal to 1.29,

M is the molar mass of the natural gas (g/mol),

R is the molar gas constant (J/(mol·K)),

T is the temperature of the natural gas (K).

Q_E is the emergency leakage rate (kg/s),

t and t_E are the leakage time and the start time of emergency shutdown (s),

m_0 is the residual mass of the natural gas (kg),

L_D is the distance between the shut-down valve and the leakage location.

After the abovementioned configuration of the gas dispersion model, the gas leakage, dispersion, and safety barriers intervention can be well modeled and the spatiotemporal distribution of leaking gas concentration can be predicted. To validate the effectiveness of the simplified gas dispersion model, a three dimensional CFD simulation for gas leakage in utility tunnels is performed. Table 3 details the specific configuration of a three-dimensional CFD model (Ansys Fluent). The configurations applied in Ansys Fluent have been parameterized into our proposed gas dispersion model to maintain consistency in initial and boundary conditions. Fig. 4 illustrates a comparison between the three-dimensional CFD model and our proposed one-dimensional gas dispersion model. The similar predictive trends of the two models demonstrate that the one-dimensional gas dispersion model can reflect the distribution and magnitude of gas concentration in utility tunnels.

Table 3
Configuration of the three dimensional CFD model.

Parameter	Value
Length of the utility tunnel (m)	200
Width of the utility tunnel (m)	2
Height of the utility tunnel (m)	2.4
Location of leakage hole (m)	(30, 0.9, 0.6)
Diameter of leakage hole (mm)	50
Diameter of the gas pipeline (mm)	500
Ventilation rate (m/s)	1.6
Leakage rate (m/s)	50
Environmental temperature (K)	293

To evaluate the possible explosion consequence of gas leakage accidents and its destructive effect on the utility tunnel, the equivalent cloud method is employed to convert the inhomogeneous gas concentration to vapor cloud volume of stoichiometric concentration, which can then be integrated to predict the explosion overpressure by using Baker-Strehlow model. In this study, a novel equivalent cloud method proposed by Zhang et al., [32] is utilized. The specific formulas and calculation process of this method are listed as follows:

$$\boldsymbol{CV}_1(\boldsymbol{j}) = \boldsymbol{CV}_0 \cdot \left[\frac{\boldsymbol{S}_0(\boldsymbol{ER})}{\boldsymbol{S}_1(\boldsymbol{ER})}\right]^{2.945} \tag{7}$$

$$\boldsymbol{V}_{stoi} = \sum_{j=1}^{N} \boldsymbol{CV}_1(\boldsymbol{j}) \tag{8}$$

Where

$CV_1(j)$ is the volume of equivalent gas cloud corresponding to the jth grid in the gas dispersion model (m^3),

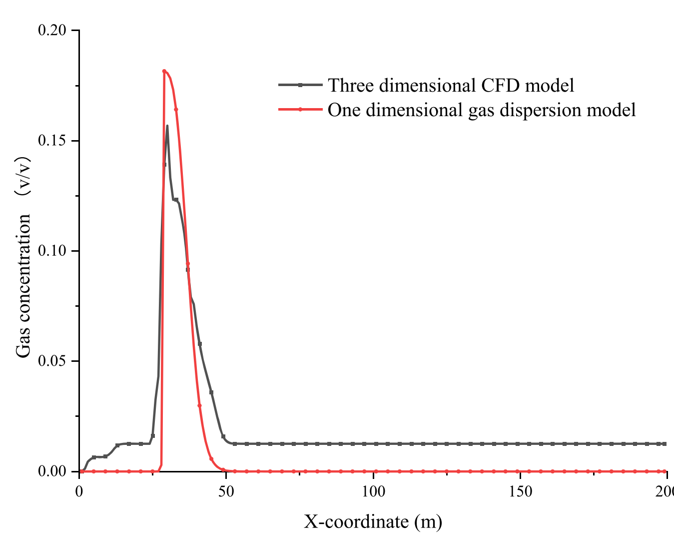

Fig. 4. Validation of the one-dimensional gas dispersion model.

CV_0 is the volume corresponding to the jth grid (m^3),

ER is the equivalent ratio of corresponding gas concentration, *Cantera* tool is used to achieve this conversion [33],

$S_0(ER)$ is the laminar burning velocity corresponding to the gas concentration at the jth grid (m/s), which can be obtained by a quantitative relationship between laminar burning velocity and ER in Fig. 5,

$S_1(ER)$ is the laminar burning velocity corresponding to the stoichiometric concentration of natural gas (m/s),

V_{stoi} is the total volume of equivalent gas cloud corresponding to the stoichiometric concentration (m^3),

N is the total number of grids used in the gas dispersion model.

Finally, the obtained V_{stoi} will be combined with the Baker-Strehlow model considering the structural features of utility tunnels [35,36]. The Baker-Strehlow model first determines the flame Mach numbers based on the fuel reactivity, obstacle density, and flame expansion, as shown in Table 4. Then, the explosion overpressure can be calculated by formulas (9) to (11). And the predicted overpressure can be taken as the reference for quantitatively evaluating the destructive effect on the utility tunnel.

$$\overline{P} = 0.411 \cdot \overline{R}^{-0.924} \tag{9}$$

$$\overline{R} = R \cdot \left(\frac{P_0}{E}\right)^{1/3} \tag{10}$$

$$E = V_{stoi} \cdot f \tag{11}$$

Where

$\overline{P}$ is the explosion overpressure and P_0 is the atmospheric pressure (Mpa),

$\overline{R}$ is the dimensionless distance and R is the distance to explosion center (m),

E is the total energy released from the gas explosion (J),

f is the combustion heat of the natural gas (KJ/m^3).

2.3.3. Risk index construction

This section proposes two risk indexes that enable quantitative risk assessment of all-process accident scenarios in utility tunnels, including the cumulative risk and cascading risk index. These indexes will also be used to support risk-based barrier optimization, as described in the following section. The duration of the explosive gas cloud is a critical index to represent the risk level of gas leakage accidents in the natural gas compartment [10,2]. Based on the developed leakage scenario set and probability analysis in Section 2.2, the cumulative risk index, therefore, can be constructed by introducing the probability weight into the duration of the explosive gas cloud corresponding to the specific leakage scenario, as shown in the Formulas (12) and (13).

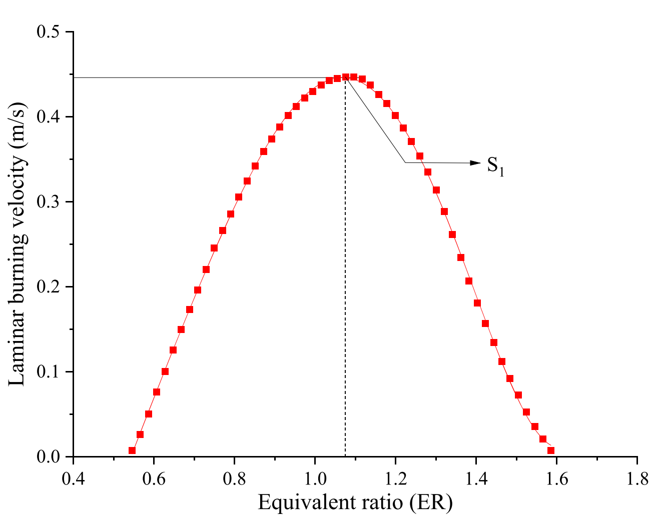

Fig. 5. Relationship between laminar burning velocity and ER [34].

Table 4
Flame Mach numbers M_w for various explosion scenarios [37].

Flame expansion	Fuel reactivity	Obstacle density		
		High	Medium	low
1D	High	5.200	5.200	5.200
	Medium	2.270	1.770	1.030
	low	2.270	1.030	0.294
2D	High	1.770	1.030	0.588
	Medium	1.240	0.662	0.118
	low	0.662	0.471	0.079
	High	0.588	0.153	0.071
3D	Medium	0.206	0.100	0.037
	low	0.147	0.100	0.037

$$R_L(i) = \left(P_L(i) \Big/ \sum_{1}^{N_L} P_L(i)\right) \cdot t_D(i) \tag{12}$$

$$R_{cum} = \sum_{1}^{N_L} R_L(i) \tag{13}$$

Where

$R_L(i)$ is the risk index corresponding to the leakage scenario i,

$t_D(i)$ is the duration of the explosive gas cloud in the leakage scenario i, and it is used to represent the consequence of leakage accidents in this study,

R_{cum} is the cumulative risk of the entire leakage scenario set.

The cascading event is further defined to represent the unacceptable accident consequence in the natural gas compartment of utility tunnels. By referring to the failure pressures of structural building elements in Table 5 and previous study on the structural damage of utility tunnels under gas explosion loads ([38]b), we regard the overpressure of 0.25 Mpa as the triggering condition of cascading events because concrete walls can suffer cracks or damage under this blast loading. Therefore, other compartments adjacent to the natural gas compartment will be affected. Meanwhile, the cascading risk is defined to indicate the proportion of unacceptable events in the leakage scenario set, which is presented in Formula (14) as follows:

$$R_{cas} = \frac{N_{cas}}{N_L} \tag{14}$$

$$R_{cas} = \begin{cases} 0, & for\ prevention \\ a, & for\ mitigation \end{cases} \tag{15}$$

Where

R_{cas} is the cascading risk of gas leakage accidents in utility tunnels,

N_{cas} is the number of unacceptable events in the leakage scenario set,

a is a preset constant to represent an acceptable level of cascading risk decided by decision-makers or managers. When it equals zero, it signifies that any unacceptable events are rejected. Conversely, when it is set to a specific value, it indicates that cascading risk below that threshold is considered acceptable.

2.4. Risk-based optimization

The tradeoff between safety investment and risk-reduction performance of safety barriers is always a critical issue that should be addressed in the decision-making phase [41,42]. In this section, the optimization objective and optimization constraints are analyzed and the implementation of the genetic algorithm helps to solve the well-defined optimization problem.

2.4.1. Analysis of optimization constraints

Typically, a safety optimization problem should satisfy one or multiple constraints, which may be a minimum safety level and/or the

Table 5
Failure pressures of structural building elements under gas explosion conditions [39,40].

Degree of destruction	1	2	3	4	5	6	7
Degree name	Basically no damage	Secondary mild damage	Mild damage	Moderate damage	Secondary serious damage	Severe damage	Complete damage
Overpressure, 105 Pa	< 0.02	0.02–0.09	0.09–0.25	0.25–0.40	0.4–0.55	0.55–0.76	> 0.76
Glass	Accidental damage	Little damage	Most damage or smash	Smash	/	/	/
Wooden window	No damage	Slightly damaged	Mostly damaged	Severely damaged	All destroyed	/	/
Wooden wall	No damage	No damage	Panel deformation	Broken wood sandalwood	Accidental breakage of panels	Partially collapsed	All collapsed
Tile roof	No damage	Little movement	Mass movement	All lift	/	/	/
Brick wall	No damage	Plaster falls slightly	Plaster falls severely	Small crack	Large crack	Severe crack, partially collapsed	Most collapsed
Reinforced concrete column	No damage	No damage	No damage	No damage	No damage	Tilt	Large tilt

maximum safety investment budget. According to the genetic algorithm, some key variables should be set to perform an optimization in practice, such as the objective function, constraints, and decision variables. In this study, the decision variables are the performance parameters of the emergency response systems (e.g., the layout of gas sensors, the ventilation rate of the variable ventilation fan, et al.). Concerning the costs of each safety barrier, we assume the requirement regulated by *Technical Specification for Urban Utility Tunnel Engineering (GB 50838–2015)* is the reasonable budget criterion: (i) the minimum installation distance between each combustible gas sensor is not smaller than 15 m. (ii) the maximum ventilation rate is not larger than 18 times/h. With such regulation, the costs associated with the installation investment of combustible gas sensors and the power consumption of ventilation fans are constrained. Based on the developed risk indexes, the objective function is set as minimizing the cumulative risk, and the constraint is set as the cascading risk. Therefore, the safety optimization problem becomes pursuing the minimum cumulative risk level inside the natural gas compartment, while preventing or mitigating possible cascading events in entire utility tunnels.

2.4.2. *Optimization algorithm*

The Genetic algorithm is a stochastic global search method that mimics the process of natural selection to find the optimal solution to an optimization problem. GA has been proven to be feasible and effective in solving multivariable, nonlinear, and combinatorial optimization problems, including those related to the tradeoff between safety risks and costs [19,23]. The intrinsic operations of selection, crossover, and mutation in GA effectively mitigate the common issue of local optima in optimization methods. This leads to quicker convergence with fewer iterations. GA's ability to accommodate various constraints and

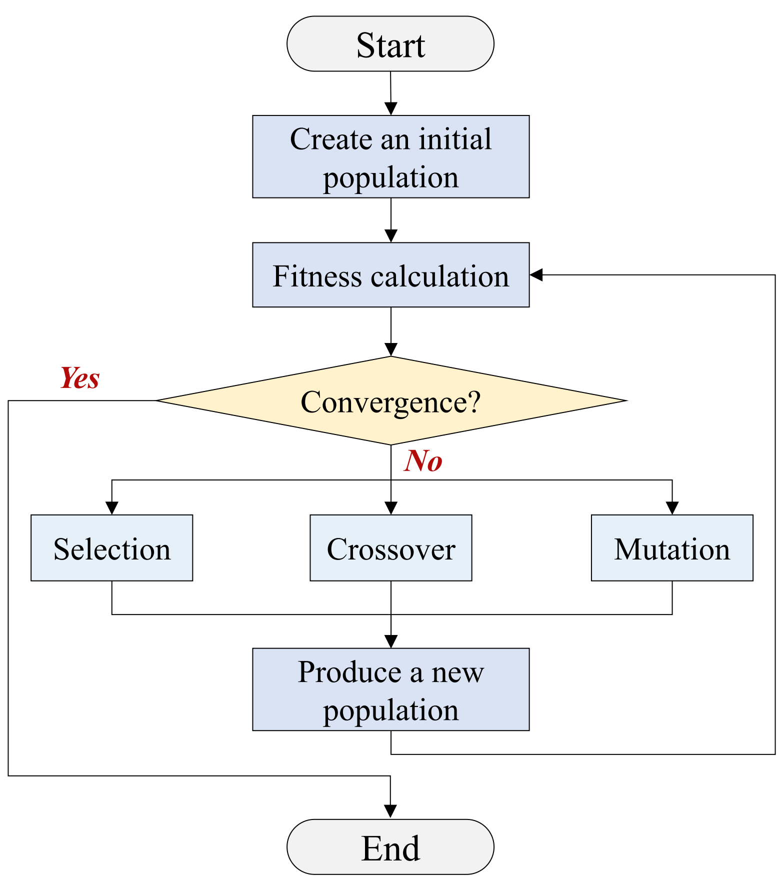

Fig. 6. Logic flow chart of the genetic algorithm.

objective functions, such as the diverse risk indices in this study, facilitates its integration with other methods.

Fig. 6 illustrates the scheme of the genetic algorithm used in this study. The GA starts by creating a population of potential solutions/ decision variables, which in this case are safety barriers. At each generation, GA iteratively improves this population through the operators of selection, crossover, and mutation. This algorithm evaluates the fitness of each potential solution, and those with higher fitness are more likely to be selected for reproduction, while less fit solutions are eliminated. This process leads to the creation of subsequent generations of the examined population better suited to their environment than their parents. Through repeated generations of reproduction, the algorithm converges towards a solution that optimizes the objective function being minimized or maximized [43]. In this study, the GA minimizes the objective function (*Rcum*) under the risk constraint (*Rcas*) and determines the optimal strategy of potential solutions, which can be found in the Formula (16). Meanwhile, the investment costs of safety barriers are implicitly involved in considering the specific requirements of *Technical Specification for Urban Utility Tunnel Engineering (GB 50838–2015)* [5].

$$\begin{cases} \dfrac{Min(R_{cum}}{R_{cas} = 0\, or < R_{cas} \le a} \end{cases} \tag{16}$$

3. Case study

Based on the proposed approach, an illustrative case study is implemented to demonstrate the feasibility and advantages of the proposed approach. This case study is elaborated in three parts: (i) configurations of the proposed approach, (ii) comparison between current strategies and optimized strategies of safety barriers, (iii) advantage analysis of safety barriers optimization using the proposed approach.

3.1. Configurations

The physical model of a typical natural gas compartment of utility tunnels is illustrated first, along with the configuration of related safety barriers. As shown in Fig. 2, the natural gas compartment is built as a tunnel structure with a variety of facilities. The specific configuration of the natural gas compartment is determined by referring to the underground utility tunnel of Changbin Road in Haikou City. The detailed parameters are presented in Table 6.

In terms of risk modeling, the configurations of the developed rapid consequence prediction model are elaborated. Then, the risk modeling can be achieved by using the risk indexes proposed in Section 2.3. In the simulation of gas leakage and dispersion, the boundary conditions are configured and listed as follows:

(i) Ventilation vent: a time-dependent Dirichlet boundary condition is employed to mimic the dynamic transformation of ventilation speed. Based on the Formula (3), the ventilation speed can be set as 1.6 m/s and 3.2 m/s for normal and accidental scenarios respectively.

(ii) Leakage source: a time-dependent Dirichlet boundary condition is used to mimic the decrease of leakage rate due to the shut-down valve activation. Based on the Formulas (4)–(6).

In the simulation process of ignition and gas explosion, the predicted inhomogeneous gas cloud is converted to an equivalent vapor cloud volume of stoichiometric concentration using Formulas (7), (8). The maximum volumes of equivalent vapor clouds in the time series are assumed to be ignited at the center of this gas cloud, representing a worst-case in gas explosion scenarios. Based on the fuel reactivity (low), obstacle density (medium), and flame expansion (1D) of the natural gas compartment, a Flame Mach number *Mw* of 1.03 can be determined from Table 4. This number is used to obtain a deterministic relation between dimensionless distance and explosion overpressure according to Formulas (9)–(11).

In terms of genetic algorithms, the ventilation rate and layout of gas sensors are considered to be optimized and improved simultaneously. The reason for the unavoidable ignorance of shut-down valves is that we only consider a 200 m compartment of the utility tunnel. But the distance between two shut-down valves usually exceeds several kilometers. Finally, a total of 14 decision variables are chosen to represent the performance parameters of safety barriers in utility tunnels, as shown in formula (16), the value of n and xi range from 12–18 to 0–200, respectively [5].

$$\langle n, x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13} \rangle \tag{17}$$

Where

n is the ventilation rate of the ventilation fan in emergency scenarios (times/h),

x_i is the possible location of the specific gas sensor (m), a total of 13 sensors are considered to be optimized.

3.2. Sensitivity analysis

In this section, we investigate the sensitivity of various factors in our proposed model. We examine the impact of different leakage locations and leak hole sizes on cumulative risks. Additionally, we incorporate the initial distribution of optimized variables and the constraints on acceptable cascading risk to demonstrate the robustness and effectiveness of our model. Fig. 7 illustrates the influence of diverse leakage locations and sizes on cumulative risks. It is observed that the cumulative risk tends to decrease with an increase in the leakage location. This trend is attributed to the fact that a leakage location in the upwind direction represents a longer dispersion distance, increasing the likelihood of forming an explosive gas cloud. Furthermore, smaller leak hole sizes contribute to a relatively larger cumulative risk due to their higher occurrence and ignition probabilities. Tables 7 and 8 present the sensitivity analysis of the initial distribution of optimized variables (namely, ventilation rate and sensor layout) and the constraint of acceptable cascading risk (defined as the permissible number of accidents in a total of 117 leakage scenarios). Despite varying initial distributions of optimized variables and constraints on acceptable cascading risk, our proposed approach consistently converges to a relatively low cumulative risk by optimizing the ventilation rate and sensor layout. This finding indicates that our approach is resilient to initial distribution variances and is capable of identifying a relatively optimal solution for mitigating accident risk under various leakage scenarios and decision-making preferences.

3.3. Results and comparative analysis

This section makes a comparison between the risk modeling results by using the proposed approach and by using current allocation and configuration strategies of emergency response systems in utility tunnels. Fig. 8 presents the optimization results by using the proposed approach, in which penalty values indicate the cumulative risk of

Table 6
Configuration of the natural gas compartment in the utility tunnel.

Type	Parameter	Setup value
Geometry	Length of the utility tunnel (m)	200
	Width of the utility tunnel (m)	2
	Height of the utility tunnel (m)	2.4
Gas properties (Pure methane)	Natural gas temperature (K)	288
	Natural gas density (kg/m3)	0.7174
	Combustion heat (MJ/m3)	39.75
	Pressure (Mpa)	1.6
Safety barriers	Layout of gas sensors (m)	[10, 25, 40, …, 175, 190]
	Nomal ventilation rate (times/h)	6
	Evergency ventilation rate (times/h)	12
	Distance between leakage hole and shut-down valve (km)	5

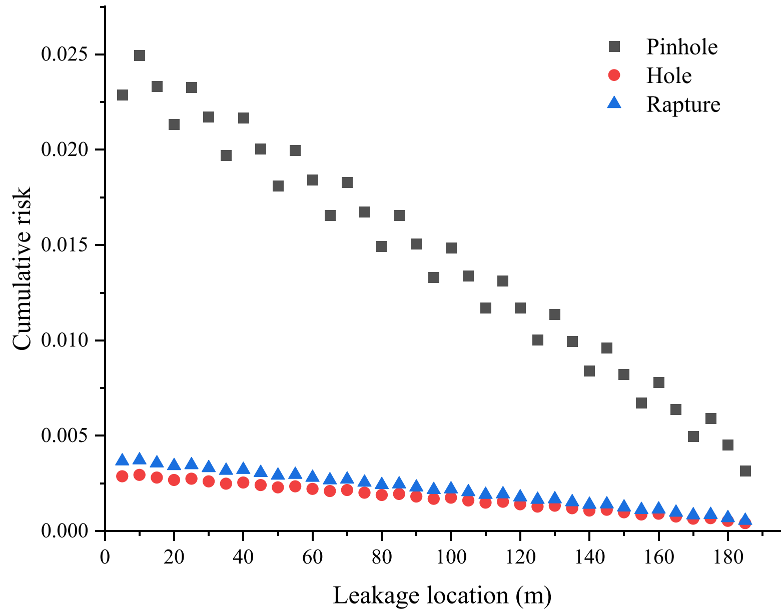

Fig. 7. Sensitivity analysis of different leakage locations and leakage sizes.

Table 7
Sensitivity analysis of the variables under optimization.

Case	Initial configurations	Cumulative risk before optimization	Cumulative risk after optimization
1	① Ventilation rate: 6 times/h ② Sensor layout: [10 m, 25 m, 40 m, 55 m, 70 m, 85 m, 100 m, 115 m, 130 m, 145 m, 160 m, 175 m, 190 m]	0.8102	0.4796
2	① Ventilation rate:12 times/h ② Sensor layout: [5 m, 15 m, 25 m, 35 m, 45 m, 55 m, 65 m, 75 m, 85 m, 95 m, 105 m, 115 m, 125 m]	0.8102	0.4785
3	① Ventilation rate:18 times/h ② Sensor layout: [75 m, 85 m, 95 m, 105 m, 115 m, 125 m, 135 m, 145 m, 155 m, 165 m, 175 m, 185 m, 195 m]	0.8102	0.4791

Table 8
Sensitivity analysis of optimization constraints.

Case	Constraints regarding acceptable cascading risk	Cumulative risk before optimization	Cumulative risk after optimization
1	0.0256 (3 cascading event in 117 leakage scenarios)	0.8102	0.4767
2	0.0427 (5 cascading event in 117 leakage scenarios)	0.8102	0.4788
3	0.0598 (7 cascading event in 117 leakage scenarios)	0.8102	0.4786

accident scenarios in genetic evolution. The best penalty value (i.e., the optimal strategy of the emergency response system) is 0.4767 and it takes approximately 70 generation iterations to converge. This demonstrates a superiority over the mean penalty value of 1.376 at the end of generation iterations, with a relative improvement of approximately 65.36 %. Table 9 presents the optimal strategy for safety barriers corresponding to the best penalty value, in which the optimal ventilation rate and layout of each gas sensor are provided. As shown in Table 9, the optimal ventilation rate is optimized to 17.71 times/h approaching the maximum ventilation rate (18 times/h) in the natural gas compartment. This is because a larger ventilation rate helps to accelerate the dilution efficiency of the leaking gas cloud. Meanwhile, the larger ventilation rate promotes the gas cloud to approach the downstream ventilation outlet quickly. This finally causes a shorter duration of the explosive gas cloud in the natural gas compartment, and therefore a smaller cumulative risk. For the layout of gas sensors, a distinct strategy is found by using the proposed approach compared to the current strategy with uniform intervals between gas sensors. According to the optimization results, it is recommended to distribute more gas sensors upwind, and a non-uniform interval is deemed ideal. This strategy significantly improves the effectiveness of risk reduction but without extra investment in gas sensors. The reason for this might be that an upwind leakage usually has a long dispersion distance in the natural gas compartment, due to being far away from the ventilation outlet. In the process where air and natural gas are mixed, it has a higher likelihood of the formation and persistence of an explosive gas cloud. Therefore, it is regarded as a more dangerous accident and should be timely detected by gas sensors. A similar non-uniform strategy of gas sensors was also investigated by Bai et al., [16] and an optimistic outcome was reported, which demonstrates the feasibility of the proposed approach.

Fig. 9 compares the effectiveness of risk reduction by employing the current strategy (Ventilation rate: 12 times/s; Sensor layout: uniform intervals) with the optimized strategy (Ventilation rate: 17.71 times/s; Sensor layout: non-uniform intervals). An obvious decrease in risk level can be observed when the optimized strategy is employed, with 41.06 % for cumulative risk and 66.71 % for cascading risk respectively. It means that a shorter duration of the explosive gas cloud and a lower probability of cascading events can be achieved across all considered leakage scenarios by using the optimized strategy, which indicates the effectiveness and practicability of the proposed approach.

3.4. Advantage of the proposed approach

In the above section, systematic optimization for both ventilation rate and sensor layout is conducted. To further demonstrate the advantages of risk reduction by using the proposed approach, two single improved strategies from the current strategy are designed, as shown in Table 10. In Case 1, the ventilation rate of the current strategy is

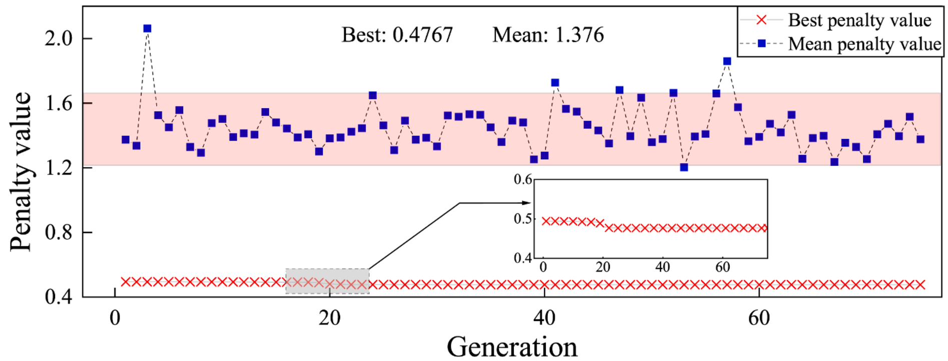

Fig. 8. Optimization results of cumulative risk.

Table 9
Optimization results of safety barriers.

Decision variables	Optimized results	Decision variables	Optimized results
n (times/h)	17.71	x_7 (m)	66
x_1 (m)	22	x_8 (m)	75
x_2 (m)	29	x_9 (m)	83
x_3 (m)	33	x_{10} (m)	115
x_4 (m)	36	x_{11} (m)	135
x_5 (m)	46	x_{12} (m)	161
x_6 (m)	55	x_{13} (m)	195

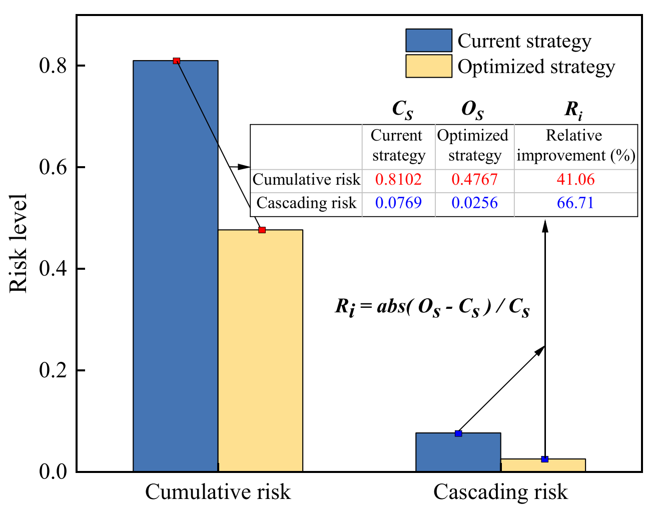

Fig. 9. Comparison between current strategies and optimized strategies.

Table 10
Optimization results of safety barriers.

	Improved strategy		Optimized strategy	
Safety barriers	Ventilation rate	Sensor layout	Ventilation rate	Sensor layout
Case 1	17.71	Uniform intervals	17.71	Non-uniform intervals
Case 2	12	Non-uniform intervals	17.71	Non-uniform intervals

improved based on the optimized strategy, while the sensor layout is improved in Case 2. The comparative results of these two cases are presented in Figs. 10 and 11. As shown in Fig. 10, the improved strategy contributes to the effective reduction of cumulative risk compared to the current strategy, but a larger cascading risk is observed. Finally, the optimized strategy also has a better performance in terms of cumulative

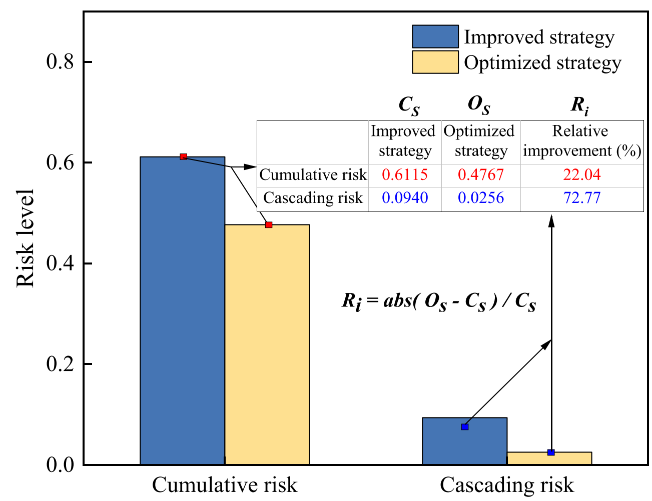

Fig. 10. Comparison between improved strategies (Ventilation rate) and optimized strategies.

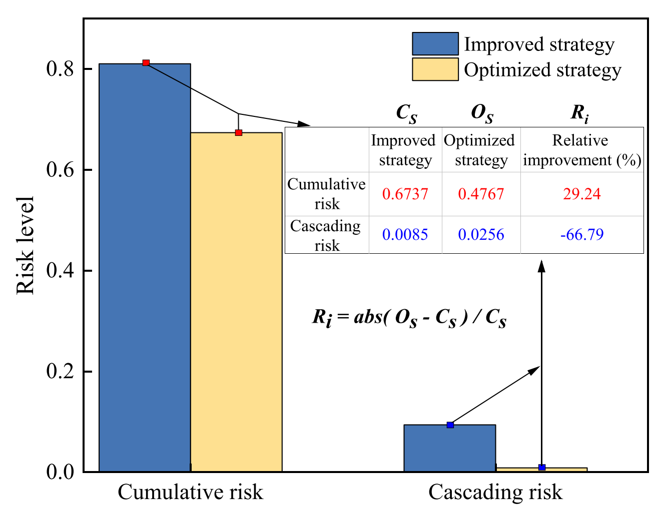

Fig. 11. Comparison between improved strategies (Sensor layout) and optimized strategies.

risk and cascading risk. Fig. 11 shows some different phenomena that the improved strategy helps to reduce both cumulative and cascading risk. Its mitigation performance in cascading risk is superior to the optimized strategy but has some drawbacks in cumulative risk. This may be the case because we take a more tolerant criterion ("a" in the Formula (15) is set as 3) for cascading risk to avoid a too strict constraint, preventing the comprehensive search for potential solutions. The optimization algorithm regards a cascading risk of 0.0256 (3 cascading events in a total of 117 leakage scenarios) as acceptance, and therefore put more effort to minimize cumulative risk as much as possible. From the perspective of the gas leakage and dispersion process, a relatively large ventilation rate (17.71 times/h) might help the mix of leaking gas and form a larger explosive gas cloud, which causes more possible cascading events.

Overall, risk reduction by using the combination of various safety barriers is a complex and nonlinear problem. For example, increasing ventilation rates accelerates dilution efficiency but also increases the risk of producing a larger volume of explosive gas clouds. The interactions between different safety barriers and the implementation degree of each barrier further add to the complexity of this optimization process. Therefore, the proposed approach has a significant advantage in addressing these issues, and it is recommended to use a systematic optimization instead of a single optimization.

4. Conclusion

This study proposed a risk-based optimization approach for various safety barriers in the natural gas compartment of utility tunnels. Based on the probability analysis and a newly developed consequence rapid prediction model (CRPM), two risk indexes are defined to represent the risk level of the natural gas compartment and multi-compartment. Finally, the systematic optimization of the ventilation rate and sensor layout is achieved with good feasibility and practicability. The main conclusions and new funding are summarized as follows:

(i) The developed consequence rapid prediction model integrates the gas dispersion model, equivalent gas cloud model, and Baker-Strehlow model into one framework considering the structure characteristic of the natural gas compartment. The results indicate that it is applicable in the modeling of gas leakage and dispersion, safety barriers intervention, ignition and explosion.

(ii) The cumulative risk index is defined based on the probability-weighted results obtained from the consequence rapid prediction model that simulated a total of 117 possible leakage scenarios. The cascading risk index is designed to describe the structure damage effect by referring to the failure pressures of structural building elements. With such two risk indexes, the risk level in the natural gas compartment and entire utility tunnels can be measured.

(iii) Systematic optimization is recommended instead of a single optimization of the specific safety barrier considering the complex physical process and the interactions between different safety barriers. The optimization results show that the combination of a ventilation rate of 17.71 times/h and non-uniform distribution of gas sensors has good efficacy for risk reduction purposes.

CRediT authorship contribution statement

Jitao Cai: Writing – original draft, Methodology, Conceptualization. **Jiansong Wu:** Writing – review & editing, Supervision, Resources, Conceptualization. **Shuaiqi Yuan:** Software, Methodology, Data curation. **Genserik Reniers:** Writing – review & editing, Formal analysis. **Yiping Bai:** Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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