

Article

IDSS-Driven Quantitative Risk Assessment and Dynamic Evacuation Routing for Train Fires in Railway Bridge–Tunnel Connection Sections

Xihao Lin ^{1,2} and Xu Xin ^{3,*}

¹ State Key Laboratory of Disaster Reduction in Civil Engineering, Tongji University, Shanghai 200092, China; 2310435@tongji.edu.cn

² Department of Geotechnical Engineering, College of Civil Engineering, Tongji University, Shanghai 200092, China

³ Department of Logistics and Maritime Studies, Faculty of Business, The Hong Kong Polytechnic University, Hung Hom, Hong Kong Special Administrative Region, Hong Kong, China

* Correspondence: xu-david.xin@connect.polyu.hk

Abstract

Train fires in railway bridge–tunnel connection sections (BTCs) create severe evacuation challenges because tunnel–bridge spatial transitions interact with heat, smoke, visibility loss, and constrained rescue conditions. Existing evacuation management methods remain limited in coupling quantitative risk assessment with adaptive route guidance under evolving fire hazards. To address this issue, this paper proposes a large language model (LLM)-enhanced intelligent decision-support system (IDSS) framework for quantitative risk assessment and dynamic evacuation routing in BTC fire scenarios. First, a multi-dimensional risk assessment model is established using the analytic hierarchy process and fuzzy comprehensive evaluation to quantify post-stop evacuation risk from the perspectives of evacuation organization, structural damage, and line recovery. Second, a dynamic topology-based routing method is developed to prune fire-threatened nodes and identify safer evacuation paths under evolving hazard conditions. The risk assessment model and routing algorithm are further embedded as callable tools into an LLM-enhanced evacuation IDSS under a perception–reasoning–recommendation architecture, in which an LLM orchestrates tool invocation, situational reasoning, and recommendation generation, thereby enabling autonomous risk interpretation, dynamic route replanning, and cross-regional collaborative decision support. The proposed framework is validated through a representative real-world railway engineering case. The results show that the IDSS-recommended routes achieved higher comprehensive safety scores (80.44 and 79.56) than routes involving fire-affected areas did (77.00 and 77.88). Workflow analysis further indicates that the proposed IDSS reduces the manual route-derivation workload by integrating risk assessment, topology pruning, and route allocation into structured, human-reviewable evacuation recommendations. Expert evaluations further confirm the rationality and compliance of the outputs, with review scores ranging from 1.76 to 1.92 out of 2.00. Overall, the proposed framework offers a feasible decision-support approach for intelligent evacuation management in complex railway fire emergencies.

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1. Introduction

With the expansion of railway systems across urban, metropolitan, and regional corridors, BTCs have become increasingly common in modern rail infrastructure, particularly along lines that traverse complex terrains, rivers, and densely developed environments [1,2]. Unlike isolated tunnels or bridges, BTCs involve abrupt transitions between enclosed and open spaces, which create pronounced environmental discontinuities and complex operational interactions [3]. In train fire scenarios, evacuation in these sections is constrained not only by heat, smoke, and reduced visibility but also by site-specific conditions, such as limited rescue access in dense urban areas and hypoxia or low temperatures in plateau regions [4]. Consequently, passenger evacuation after train stoppages in railway BTCs represents a particularly challenging safety problem for modern transportation systems [5].

A substantial body of research has investigated fire safety and emergency evacuation in railway tunnels, underground spaces, and other confined transport infrastructures [6,7]. Existing studies have advanced the understanding of smoke movement [8–10], tenability evolution [11–14], evacuation behavior [15–18], and ventilation control [19–21] in tunnel fire scenarios. In parallel, bridge fire safety and post-disaster structural assessment have received increasing attention [22], especially with respect to thermal damage [23], serviceability degradation [24], and mitigation strategies [25] under extreme events, as well as emergency-response issues such as passenger evacuation behavior [26], responder access [27], and rescue safety [28]. However, most studies focus on isolated tunnels or bridges, where spatial boundary conditions and evacuation logic are relatively well defined. In contrast, BTC fire emergencies involve coupled multi-zone interactions across tunnel and bridge domains, together with more complex route accessibility, exit allocation, and hazard propagation. Therefore, conclusions derived from single-space scenarios cannot be directly transferred to railway BTC fire emergencies.

Moreover, quantitative risk assessment methods, including Delphi [29], the analytic hierarchy process (AHP) [30], and fuzzy comprehensive evaluation (FCE) [31], provide useful tools for transforming complex disaster factors into structured safety indicators. These approaches are valuable for identifying key risk sources and supporting system-level emergency planning. Nevertheless, most existing risk assessment frameworks remain essentially static. They are often used as offline evaluation tools for predefined scenarios rather than as online engines that can interact with real-time hazard evolution and evacuation control [32,33]. In practical emergency response, the value of a risk model depends not only on its ability to quantify safety conditions but also on whether its outputs can be promptly converted into actionable route planning suggestions and cross-regional decision recommendations. This methodological gap is particularly evident in BTC fire scenarios, where route availability may change rapidly because of fire proximity, smoke accumulation, structural impairment, or local congestion. In addition, path planning and evacuation optimization methods have progressed from conventional shortest-path strategies to more adaptive routing paradigms that account for dynamic environmental constraints [34]. Graph-based models [35,36], heuristic search methods [37,38], and multi-objective evacuation algorithms [39–41] have improved the ability to identify safer routes under changing conditions. However, many of these methods still depend on fixed rules, simplified hazard representations, or predetermined control logic. Their ability to address real emergency scenes remains limited, especially when continuous perception, multi-source information fusion, risk reasoning, and coordinated recommendation generation are needed.

Advances in IDSSs have created new opportunities for emergency management in complex transportation systems [42–44]. By integrating knowledge storage and retrieval, LLM-enabled reasoning and question answering, computational model invocation, and

recommendation generation within a unified architecture, IDSS can provide actionable support that goes beyond passive information retrieval [45–47]. However, applications of IDSS to civil infrastructure and fire emergency management remain limited [48,49]. Existing studies have focused mainly on emergency knowledge support [50], fire evacuation simulation [51], or human–machine interactive evacuation analysis in large infrastructures [52]. In contrast, integrated IDSS frameworks that explicitly couple quantitative risk assessment with dynamic evacuation routing for railway BTCS train fire scenarios remain scarce.

To address these gaps, we propose an LLM-enhanced IDSS framework for dynamic evacuation routing and quantitative risk assessment in railway BTCS fire emergencies from a systems engineering perspective. The framework treats evacuation as a multi-layer socio-technical process embedded in resilient transportation infrastructure. First, a multi-dimensional risk assessment model is developed to quantify post-stop evacuation risk from the perspectives of evacuation organization, structural damage, and line recovery. On this basis, a dynamic topology-based routing method is designed to identify feasible and safer evacuation paths under fire proximity and infrastructure constraints. The quantitative model and routing algorithm are then embedded into an evacuation IDSS under a perception–reasoning–recommendation (PRR) paradigm, in which the reasoning layer is implemented through knowledge-grounded LLM-based reasoning and question answering. This design enables adaptive route generation and coordinated emergency decision support. Finally, a representative engineering case is used to verify the effectiveness of the proposed framework.

The main contributions of our paper are threefold. First, a multi-dimensional quantitative risk assessment model is established for train fire evacuation in railway BTCSs, extending conventional research from single-space environments to coupled bridge–tunnel connection settings, and its quantitative outputs are used directly to drive dynamic route generation. Second, quantitative risk assessment and dynamic evacuation routing are integrated into a unified systems engineering decision framework, in which the safe subgraph is pruned based on the current fire state, and the recommended routes are recomputed as this state changes. Third, an LLM-enhanced IDSS-based decision-support approach is developed, in which the deterministic risk and routing tools produce the safety scores and routes, and the LLM orchestrates these tools and organizes their outputs into human-reviewable recommendations within a closed PRR loop.

The remainder of this paper is organized as follows. Section 2 establishes a quantitative risk assessment model for post-stop evacuation in BTCS fire scenarios. Section 3 presents the dynamic evacuation routing method under spatial and hazard constraints. Section 4 introduces the LLM-enhanced IDSS framework for evacuation decision support under the PRR paradigm. Section 5 validates the proposed approach through an engineering case study and comparative analyses. Section 6 concludes the paper.

2. Multi-Dimensional Risk Assessment Model for Post-Stop Evacuation

2.1. Selection and Hierarchical Organization of Key Risk Indicators

Under fire accident conditions, railway BTCSs are exposed to complex environmental and operational constraints. These constraints may include restricted rescue access in densely built urban corridors, low pressure, hypoxia, and low temperature along high-altitude lines, as well as the spatial and structural limitations inherent in coupled bridge–tunnel configurations. From a systems engineering perspective, the risks associated with personnel evacuation arise from natural environmental factors, structural design factors, train operation factors, and fire characteristics, which together form a multi-layer socio-technical risk structure. These primary factors are numerous and strongly correlated,

making them unsuitable for direct quantitative assessment. To satisfy the principles of relative independence and parsimony in indicator selection, these initial factors must be reconstructed and refined. Based on the full fire-evacuation process, three key indicators spanning the full course of post-stop evacuation are identified: evacuation organization, structural damage, and line recovery.

The first core risk indicator identified through this reconstruction process is evacuation organization. This indicator evaluates the direct efficiency of personnel withdrawal and the level of safety assurance during a fire. It contains three subdimensions: evacuation facility design, evacuation rescue conditions, and crowd evacuation characteristics. The evacuation facility design covers the completeness of the auxiliary alarm and route guidance equipment, as well as the rationality of the spatial layout of the evacuation passages and exits. Evacuation rescue conditions reflect the dynamic adjustment capability of emergency plans and the responsiveness of disaster response, including the activation of ventilation and smoke-exhaust control that governs smoke clearance along the evacuation route. Crowd evacuation characteristics describe the movement performance of evacuees during withdrawal, including crowd density, group speed, and total escape time. Natural environmental factors, such as plateau hypoxia and smoke toxicity, primarily affect human movement and are therefore reflected in these characteristics, especially group speed and total escape time. Together, these factors determine the smoothness and effectiveness of the dynamic evacuation process.

The second core risk indicator is structural damage. The physical structures of BTCs are highly vulnerable to thermal radiation damage during fires, which may subsequently obstruct evacuation routes. This indicator is further divided into non-strength damage and strength damage. Non-strength damage mainly refers to visible physical deterioration, including track deformation along the railway, crack width on bridge and tunnel surfaces, and concrete spalling depth. Strength damage reflects the degradation of the mechanical performance of key load-bearing components in tunnels and bridges, including the residual strength ratio and deformation of key tie rods, suspension cables, and arch crowns. The structural-damage dimension reflects the effects of fire development on infrastructure, especially line deformation, surface deterioration, and strength degradation induced by thermal radiation and high-temperature smoke. Quantifying the level of structural damage provides a direct basis for evaluating the physical safety margin of evacuation passages.

The third core risk indicator is line recovery. Although post-disaster recovery capability is associated with the later stage of the evacuation process, it directly reflects the resilience and emergency management capacity of the affected BTC. Line recovery characterizes the post-fire recoverability of the affected section and the emergency management conditions supporting evacuation implementation. This indicator includes two sub-items, namely bridge–tunnel damage recovery and train operation recovery. Bridge–tunnel damage recovery evaluates the damage resistance and recoverability of key bridge–tunnel components and line facilities after fire damage, with repair difficulty and expected restoration time as supporting criteria. Train operation recovery considers disaster organization management and fire information integration, including equipment utilization, emergency plan completeness, emergency drill frequency, safety management optimization, and the efficiency of real-time disaster information integration and transmission. Of these, Emergency drill frequency reflects preparedness and emergency handling capacity rather than directly determining an evacuation route. The incorporation of line recovery capability supports the closed-loop management of cross-regional evacuation plans.

By systematically organizing the multi-dimensional risk sources described above, this paper employs the AHP to establish a multi-dimensional risk assessment model for train fire scenarios in BTCs, as shown in Table 1. Structurally, the model consists of four

progressively refined levels: the target layer, criterion layer, indicator layer, and rating layer. The target layer represents the overall risk (R) of post-stop evacuation in train fire accidents, and the quantified value of R provides a safety basis for comparing candidate exits and evacuation routes in the subsequent IDSS routing process. The criterion layer includes three core dimensions: evacuation organization (R_1), structural damage (R_2), and line recovery (R_3). The indicator layer further specifies each criterion according to its characteristics, thereby providing a direct basis for risk assessment. The rating layer provides detailed scores for each indicator, with the scoring criteria mainly determined by engineering experience and relevant codes and standards. Through this four-level structure, the proposed assessment model transforms complex evacuation risk sources into a systematic evaluation framework, thereby supporting subsequent quantitative analysis.

Table 1. Hierarchical index system for post-stop evacuation risk assessment in BTCS fire scenarios.

Target Layer	Criterion Layer	Indicator Layer	Rating Layer
Post-stop evacuation risk (R)	Evacuation organization (R_1)	Evacuation facility design (R_{11})	Evacuation equipment (R_{111})
			Evacuation passage (R_{112})
			Evacuation exit (R_{113})
		Evacuation rescue conditions (R_{12})	Evacuation plan (R_{121})
			Disaster response (R_{122})
			Evacuation mode (R_{123})
	Structural damage (R_2)	Crowd evacuation characteristics (R_{13})	Crowd density (R_{131})
			Group speed (R_{132})
			Evacuation time (R_{133})
		Non-strength damage (R_{21})	Line damage (R_{211})
			Surface damage (R_{212})
			Internal damage (R_{213})
	Line recovery (R_3)	Strength damage (R_{22})	Tunnel strength damage (R_{221})
			Bridge strength damage (R_{222})
			Structural damage recovery (R_{311})
		Bridge–tunnel damage recovery (R_{31})	Line damage recovery (R_{312})
			Disaster organization management (R_{321})
			Train operation recovery (R_{32})
			Fire information integration (R_{322})

2.2. Establishment of the Quantitative Risk Assessment Model

Based on the constructed multi-dimensional risk assessment framework, this paper further employs the FCE method to establish a post-stop evacuation risk assessment model for train fire scenarios in BTCSs. This model transforms qualitative judgments into quantitative safety scores. The procedure for constructing and mathematically solving the proposed model consists of five main steps: establishing the factor set, defining the evaluation set, constructing the membership matrix, determining the weight set, and calculating the comprehensive evaluation result. Within the overall process, the AHP-based expert elicitation converts expert judgment into an indicator-weighting system, which is stored in the IDSS's long-term memory, while the FCE serves as a deterministic aggregation module that combines the weight vectors with scenario-specific indicator scores to produce route-level safety scores. The weight system is a reusable structural prior for post-stop evacuation under BTCS train fire conditions rather than a universal constant. It can be re-elicited through the same procedure for a substantially different line or scenario.

The first step is to establish the factor set, which represents the risk attributes of the evaluated object. According to the evaluation index system defined in Table 1, the target

layer is decomposed into a factor set U containing three sub-criteria, as shown in Equation (1). These sub-criteria correspond to evacuation organization, structural damage, and line recovery, respectively.

$$U = \{u_1, u_2, u_3\}. \quad (1)$$

Owing to the hierarchical structure of the assessment system, each factor u_i can be further decomposed into a lower-level sub-factor set, as expressed in Equation (2), where i denotes the index of the factor in the current upper-level factor set, and m_i represents the number of sub-factors under u_i and may differ across upper-level factors.

$$u_i = \{u_{i1}, u_{i2}, \dots, u_{im_i}\}. \quad (2)$$

The second step is to establish the evaluation set, which is used to classify the safety status of each risk factor during the assessment process. This paper adopts a 100-point safety score system and maps the score intervals to five risk grades: extremely low risk (I), low risk (II), medium risk (III), high risk (IV), and extremely high risk (V). The corresponding safety score intervals are 80–100, 60–80, 40–60, 20–40, and 0–20, respectively. A higher safety score indicates stronger disaster resilience of the bridge–tunnel system and a safer evacuation environment.

Within the multi-level evaluation system, a strict mathematical mapping exists between the factor set and the evaluation set at each level. Taking the criterion layer as an example, because the target layer is decomposed into three core factors, the corresponding evaluation set of the criterion layer can be expressed as

$$V = \{V_1, V_2, V_3\}. \quad (3)$$

Similarly, this mapping relationship can be derived layer by layer down to the lowest rating layer. The detailed scoring basis and state quantification criteria for each indicator in the rating layer are listed in Table 2. In accordance with the scoring rules provided in this table, each bottom-level element in the rating layer can be objectively scored. After the initial scores of the bottom-level indicators are obtained, fuzzy synthesis is performed through subsequent matrix operations, and the quantitative safety score of post-stop evacuation is then derived hierarchically from the bottom up.

A membership matrix is subsequently constructed to quantify the correspondence between each evaluation factor and each risk grade. In this paper, structured expert scoring is used to obtain expert evaluations of the indicators in the rating layer. Suppose that N experts participate in the scoring process, among whom n_{ij} experts assign the i -th bottom-level evaluation factor to the j -th risk grade. The membership degree r_{ij} then represents the degree to which the i -th bottom-level factor belongs to the j -th risk grade and can be calculated using the following Equation (4):

$$r_{ij} = \frac{n_{ij}}{N}. \quad (4)$$

Based on this calculation, the membership vector of each lower-level factor can be obtained, and the fuzzy relation matrix R_i associated with the i -th upper-level indicator can then be formed, as shown in Equation (5). The element r_{ijk} in R_i represents the membership degree of the j -th lower-level sub-factor under the i -th upper-level indicator with respect to the k -th risk grade, where i denotes the index of the upper-level indicator, j represents the index of the lower-level sub-factor, and k is the index of the risk grade in the evaluation set. The matrix R_i has m rows and five columns, where m represents the number of lower-level sub-factors contained under the i -th upper-level indicator, and the five columns correspond to the five risk grades. Through this process, fuzzy judgments

that originally depend on experience-based descriptions are transformed into computable membership relationships, thereby supporting subsequent comprehensive calculations.

$$R_i = \begin{bmatrix} r_{i11} & r_{i12} & r_{i13} & r_{i14} & r_{i15} \\ r_{i21} & r_{i22} & r_{i23} & r_{i24} & r_{i25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{im1} & r_{im2} & r_{im3} & r_{im4} & r_{im5} \end{bmatrix}. \quad (5)$$

Table 2. Classification and evaluation criteria of post-stop evacuation risk grades.

Risk Grade	Score Range	Evaluation Description	Evaluation Criteria
I	$80 \leq v \leq 100$	Extremely low risk	The evacuation equipment and facilities in the BTCS are complete, functioning properly, and possess a certain degree of fault tolerance. Occupants can receive intelligent and timely evacuation guidance, and the evacuation process is rapid and orderly. Damage to the tunnel and bridge is insignificant, with only minimal structural damage. Damage to the railway line on which the train is located is negligible, recovery is straightforward, and normal operation can be restored within a short time.
II	$60 \leq v < 80$	Low risk	The evacuation equipment and facilities in the BTCS are complete and can function normally. Occupants can receive timely evacuation guidance, and the evacuation process is relatively orderly. Damage to the tunnel and bridge is limited, and the structural damage is minor. Damage to the railway line is slight, the recovery difficulty is low, and repair can be completed within a short time.
III	$40 \leq v < 60$	Medium risk	The evacuation equipment and facilities in the BTCS are incomplete but still usable. Occupants can receive some evacuation guidance, and the evacuation process can proceed normally. Partial damage exists in the tunnel and bridge, and the structural damage is moderate. Damage to the railway line is moderate, and recovery is not difficult, but repairs will take some time.
IV	$20 \leq v < 40$	High risk	The evacuation equipment and facilities in the BTCS are incomplete but still usable. Occupants receive little timely evacuation guidance, and the evacuation process is relatively chaotic. Multiple areas of the tunnel and bridge are damaged, and the structural damage is relatively severe. Damage to the railway line is substantial, recovery is difficult, and repairs will take a relatively long time.
V	$0 \leq v < 20$	Extremely high risk	The evacuation equipment and facilities in the BTCS are incomplete and difficult to use. Occupants cannot receive corresponding evacuation guidance, and the evacuation process is extremely chaotic. Severe damage exists at multiple locations in both the tunnel and the bridge, resulting in extremely serious structural damage. Damage to the railway line is severe, recovery is extremely difficult, and restoration cannot be completed for a long period.

After the membership matrix is determined, the factor weights for each level are established to reflect the relative contributions of different indicators to the overall post-stop evacuation risk. In this paper, the weights are derived through the AHP based on a single-round structured expert elicitation. Assuming that a given level contains m factors, the invited experts provide pairwise importance judgments for these m factors using the standard nine-point scale, and these judgments form an m -by- m pairwise-comparison matrix for that level. The normalized principal eigenvector of this pairwise-comparison matrix yields the weight vector A_i associated with the m lower-level factors under the i -th upper-level indicator, as shown in Equation (6), where the m components are nonnegative and sum to one. The consistency of every pairwise-comparison matrix is verified by its

consistency ratio (CR). Matrices with a CR not lower than 0.10 are returned to the corresponding expert for reconsideration, and questionnaires that still fail to satisfy this threshold after feedback are excluded from the final aggregation.

$$A_i = (a_{i1}, a_{i2}, \dots, a_{im}), \sum_{k=1}^m a_{ik} = 1. \quad (6)$$

Using the same procedure, the weight sets are obtained successively from the rating layer to the indicator layer, from the indicator layer to the criterion layer, and from the criterion layer to the target layer. The resulting weight system provides a more objective representation of the relative roles of different risk factors during post-stop evacuation under train fire conditions and forms the basis for subsequent layer-by-layer FCE.

Finally, the ultimate result of the FCE is obtained through hierarchical matrix operations. By successively substituting the membership matrices and the corresponding weight sets of each level into the FCE formulas given in Equations (7)–(10) and by performing the calculations in a bottom-up hierarchical manner, the FCE vectors of the rating layer, indicator layer, and criterion layer are obtained. In these equations, i denotes the index of the upper-level indicator involved in the current hierarchical synthesis; j represents the index of the lower-level sub-indicator under the i -th upper-level indicator; m is the number of lower-level sub-indicators contained under the i -th upper-level indicator, and n denotes the number of criterion-layer indicators entering the final target-layer synthesis. Specifically, the bottom-level fuzzy relation matrix R_{ij} , formed from the membership vectors r_{ijk} defined in Equation (5), is combined with the rating-layer weight vector A_{ij} via Equation (7) to yield the indicator-layer evaluation vector B_{ij} . The m vectors (i.e., $B_{i1}, B_{i2}, \dots, B_{im}$) obtained for the i -th criterion are then stacked via Equation (8) to form the indicator-layer relation matrix R_i , which is further synthesized with A_i via Equation (9) to obtain the criterion-layer vector B_i . Following the same logic, the criterion-layer relation matrix R is assembled from $B_1, B_2, \dots, B_n$ via Equation (10) and finally combined with the target-layer weight vector A via Equation (11) to yield the comprehensive evaluation matrix B .

$$B_{ij} = A_{ij} \times R_{ij}, \quad (7)$$

$$R_i = (B_{i1}, B_{i2}, \dots, B_{im})^T, \quad (8)$$

$$B_i = A_i \times R_i, \quad (9)$$

$$R = (B_1, B_2, \dots, B_n)^T, \quad (10)$$

$$B = A \cdot R = (b_1, b_2, b_3, b_4, b_5). \quad (11)$$

According to the maximum membership principle or the weighted average method, the most prominent risk contributors at the target, criterion, and indicator levels can be further identified, and the final result of the post-stop evacuation risk assessment can then be determined. These results can not only effectively reflect the overall evacuation safety level of the BTCS under the current fire scenario but also identify the principal sources of risk at different hierarchical levels, thereby providing a quantitative basis for the subsequent derivation of optimal evacuation routes and the dynamic adjustment of emergency response plans.

3. Dynamic Evacuation Routing Optimization

3.1. Topological Modeling and Spatial Constraints of Evacuation

Under the complex operational and environmental conditions of railway BTCs, optimal evacuation route planning is essentially a spatial optimization problem subject to dynamic environmental constraints. To enable IDSS-driven dynamic routing and computer-aided decision support, the complex physical space of the BTCs is first abstracted into a graph-theoretic topological network [53,54] that can be processed algorithmically. The evacuation space of the BTC is defined as an undirected graph $G = (V, E)$. Here, the node set $V = V_{door} \cup V_{exit}$, where subset V_{door} denotes the set of origin nodes corresponding to the train doors and subset V_{exit} represents the set of destination nodes corresponding to the available evacuation exits within the BTC. As the final anchors for occupant evacuation, the spatial topological distribution of exits plays a decisive guiding role in the formulation of global routing strategies. The edge set E represents the evacuation passage network connecting doors to exits or exits to other exits. For any edge $e_{ij} \in E$ in graph G , its basic weight w_{ij} is defined as the actual three-dimensional Euclidean distance between nodes i and j . Let the spatial coordinates of nodes i and j be denoted by (x_i, y_i, z_i) and (x_j, y_j, z_j) , respectively. The basic weight w_{ij} is then calculated using Equation (12). In conventional dynamic routing, the underlying algorithm follows the nearest-exit principle, driving evacuees to move along the minimum-weight edges toward the closest exit node in physical space.

$$w_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}. \quad (12)$$

However, the dynamically evolving location of the fire source constitutes the most critical constraint governing global topological connectivity. High-temperature thermal radiation and toxic smoke generated by fire can rapidly block originally designated safe routes. A distinction should be drawn between two categories of geospatial coordinates used in this model. The coordinates of the structural nodes, including train doors, evacuation exits, and cross-passages, are static and are pre-encoded from the design drawings and the line mileage system, since the physical geometry of the bridge-tunnel section does not change during an incident. Only the fire-source center evolves. Because the fire is confined to the known line corridor, its center is represented primarily as a longitudinal mileage position inferred from fixed monitoring, such as linear temperature detection, the activated alarm zone, and the reported train-stopping position. It is then mapped to the pre-encoded coordinate frame as $P_f(x_f, y_f, z_f)$, where f denotes the fire source. This model introduces a safety distance threshold, D_{safe} , to construct a risk-exclusion mechanism. This threshold is defined as a near-fire-source pruning radius used to exclude topological nodes located in the immediate vicinity of the fire source. For any node $v_i \in V$ in the network, where i denotes the node index, its spatial distance to the fire-source center P_f can be calculated using Equation (13).

$$d(v_i, P_f) = \sqrt{(x_i - x_f)^2 + (y_i - y_f)^2 + (z_i - z_f)^2}. \quad (13)$$

If this distance satisfies $d(v_i, P_f) < D_{safe}$, then node v_i and all its incident edges are identified as high-risk elements affected by the hazard and are forcibly removed from the available topological graph G . This rigid mathematical constraint ensures, at the algorithmic level, that evacuation trajectories categorically avoid the core fire zone.

In addition, the physical layout of the railway line and the current condition of the infrastructure limit the passage capacity and movement speed. A single-track BTC usually provides evacuation passages on both sides and therefore exhibits relatively high topological connectivity. In contrast, a double-track BTC is constrained by its internal

clearance envelope and often forms an asymmetric topological network, with evacuation possible only on one side. Under intense thermal loading, once a passage is suddenly interrupted by physical structural damage, such as surface concrete spalling, the corresponding edge weight is penalized to $w_{ij} \rightarrow \infty$, meaning that the path is marked as unreachable at the topological level. If an exit or door node is reported as unusable, for example, because it is blocked or out of service, the node and all its incident edges are removed from the available graph in the same way as high-risk nodes, so that it no longer serves as an evacuation anchor. Based on the above reconstruction, the route optimization problem handled by the IDSS is ultimately transformed into a search for a globally optimal matching strategy from all nodes in V_{door} to nodes in V_{exit} within a dynamically updated safe subgraph $G_{safe} \subset G$, subject to both dynamic fire-source constraints and structural capacity limitations, while simultaneously considering the nearest-exit principle and global capacity thresholds.

3.2. Development of the Dynamic Routing Algorithm

After the spatial topological network and hard constraints are defined, a dynamic optimal evacuation routing algorithm is developed. The purpose of this algorithm is to integrate, dynamically, train-status data, infrastructure topology, and the dynamic evolution of the fire source after a fire occurs. Through automated screening and graph-based optimization, it assigns passengers across carriages to safe exits via the shortest feasible routes within cross-regional BTCs. As shown in Figure 1, the algorithm's execution logic is primarily encapsulated in three progressive computational stages: information perception, high-risk node elimination, and global optimal matching.

At the initial stage of algorithm activation, the system receives the real-time basic parameters of the burning train, including the total train length L , the number of carriages N , and the starting and ending mileage coordinates of the train stopping position, denoted by M_{start} and M_{end} , respectively. Based on this information, the algorithm activates the topological graph G . If the perception system identifies the infrastructure as a single-track BTCS, the evacuation passage network on both sides is fully activated. If it is identified as a double-track BTCS, only the one-sided subnet adjacent to the safe side of the train is retained through a masking operation. Moreover, the detected fire-source center coordinates P_f , together with the train-door node set V_{door} and the evacuation-exit node set V_{exit} , are synchronously imported into the computational matrix.

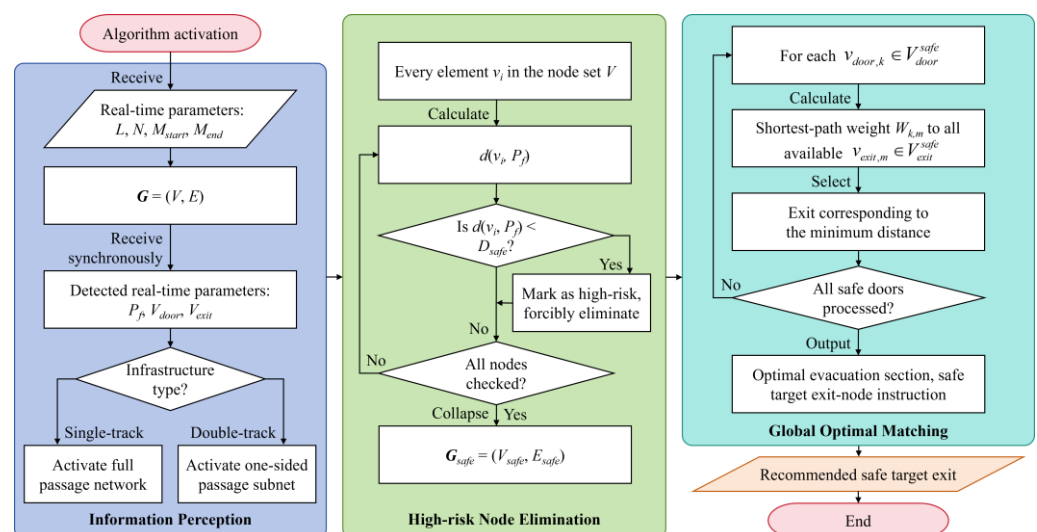


Figure 1. Execution logic of the dynamic optimal evacuation routing algorithm.

In the subsequent risk screening stage, the algorithm performs dynamic pruning of the topological graph G using the fire source P_f as the reference. Based on the safety distance threshold D_{safe} , the algorithm traverses every element v_i in node set V , including both door nodes and exit nodes. If distance $d(v_i, P_f) < D_{safe}$, the node and its associated passage edges are marked as high-risk nodes and forcibly removed from the matrix. After the pruning operation, the original network G collapses into a safe available subgraph $G_{safe} = (V_{safe}, E_{safe})$, where V_{safe} and E_{safe} denote the retained safe node set and safe edge set after fire-risk pruning, respectively, thereby preventing evacuees from being guided into the fire-affected core area at the source.

In the final matching and optimization stage, the algorithm determines the optimal mapping between the remaining door set V_{door}^{safe} and exit set V_{exit}^{safe} within the safe subgraph G_{safe} . For each safe door node $v_{door,k} \in V_{door}^{safe}$, the algorithm calculates the shortest-path weight $W_{k,m}$ to all available safe exits $v_{exit,m} \in V_{exit}^{safe}$, where k denotes the index of the safe door node, and m represents the index of the available safe exit node. Let $\pi_{k,m}$ denote the set of edges constituting the shortest path from safe door node k to safe exit node m in G_{safe} . The shortest-path weight $W_{k,m}$ is obtained by summing the basic edge weights w_{ij} along the shortest feasible path connecting node k to node m within the safe subgraph G_{safe} , as expressed in Equation (14). Based on an improved nearest-exit principle, the exit corresponding to the minimum distance is selected as the optimal evacuation anchor for that door, as expressed in Equation (15). The algorithm ultimately outputs the optimal evacuation section and the corresponding recommended safe target exit for each door. The complete procedure is summarized in Algorithm 1.

$$W_{k,m} = \sum_{(i,j) \in \pi_{k,m}} w_{ij}, \quad (14)$$

$$v_{exit}^* = \arg \min_{v_{exit,m} \in V_{exit}^{safe}} \{W_{k,m}\}. \quad (15)$$

The dominant operations of Algorithm 1 are a single pass that builds and prunes the graph at $O(|V| + |E|)$ and the door-to-exit matching that evaluates the path weight from each safe door node to each safe exit and selects the nearest one at $O(|V_{door}| \times |V_{exit}|)$. The overall cost is therefore $O(|V| + |E| + |V_{door}| \times |V_{exit}|)$. Because the train doors and local exits are few and the BTCS evacuation graph is sparse, this cost stays small and supports real-time use within the IDSS.

Algorithm 1. Dynamic optimal evacuation routing in a railway BTCS

Inputs: Topological graph $G = (V, E)$ with $V = V_{door} \cup V_{exit}$; Train length L ; Number of carriages N ; Stopping coordinates M_{start} and M_{end} ; Track type indicating a single-track or double-track BTCS; Fire-source center P_f ; Safety distance threshold D_{safe} ; Accessibility state of every passage and exit node

Outputs: Safe subgraph $G_{safe} = (V_{safe}, E_{safe})$; Recommended safe target exit v_{exit}^* and evacuation section for every safe door node

- 1: Activate graph G from the train parameters and the BTCS topology
 - 2: if the BTCS is double-track then
 - 3: apply masking and retain only the safe-side passage subnet
 - 4: end if
 - 5: for each edge e_{ij} in E do
 - 6: if the passage between nodes i and j is reported as interrupted then
 - 7: $w_{ij} \leftarrow \infty$
-

```

8:   else
9:       compute  $w_{ij}$  as the Euclidean distance between nodes  $i$  and  $j$ 
10:   end if
11: end for
12: for each node  $v_i$  in  $V$  do
13:   if  $v_i$  is reported as a failed exit or door node then
14:       remove  $v_i$  and all its incident edges
15:   else
16:       compute  $d(v_i, P_j)$ 
17:       if  $d(v_i, P_j) < D_{safe}$  then
18:           remove  $v_i$  and all its incident edges
19:       end if
20:   end if
21: end for
22: form the safe subgraph  $G_{safe}$  with the retained nodes and edges
23: for each safe door node  $k$  retained in  $G_{safe}$  do
24:   for each safe exit node  $m$  retained in  $G_{safe}$  do
25:       compute the shortest-path weight  $W_{k,m}$  on  $G_{safe}$ 
26:   end for
27:   select the exit  $v_{exit}^*$  with minimum  $W_{k,m}$ 
28:   assign door node  $k$  to exit  $v_{exit}^*$  and record the corresponding evacuation section
29: end for
30: return  $G_{safe}$  and the door-to-exit assignment for all safe door nodes

```

4. IDSS-Driven Evacuation Decision-Support Framework

4.1. Architecture of the Evacuation IDSS

To achieve integrated computer-aided decision support for evacuation risk assessment and route planning in train fire scenarios within BTCSs, this paper develops an evacuation IDSS based on the PRR paradigm. Rather than simply combining conventional alarm, broadcasting, and dispatching functions, the proposed architecture embeds the multi-dimensional risk assessment model and the dynamic optimal evacuation routing algorithm developed in the preceding sections into a unified decision-support framework. Its objective is to transform heterogeneous field information into quantified risk results, feasible evacuation routes, and reviewable emergency recommendations under human supervision. After post-stop evacuation is initiated, the IDSS compares feasible exits and lower-risk paths for different passenger groups and outputs route-oriented recommendations for command review.

As shown in Figure 2, the evacuation IDSS consists of three functional layers, namely, a perception layer, a reasoning layer, and a recommendation layer. The perception layer is responsible for acquiring and structuring real-time information from the BTCS, including temperature, visibility, fire-source location, train operating status, train formation information, passenger distribution, door status, passage accessibility, and the health status of evacuation facilities. These data are further combined with the spatial parameters required by the routing algorithm, including the train length, number of carriages, stopping chainages, train-door node set, evacuation-exit node set, and fire-source center

coordinates. In this way, the perception layer converts raw monitoring and infrastructure information into structured inputs for the subsequent computational modules.

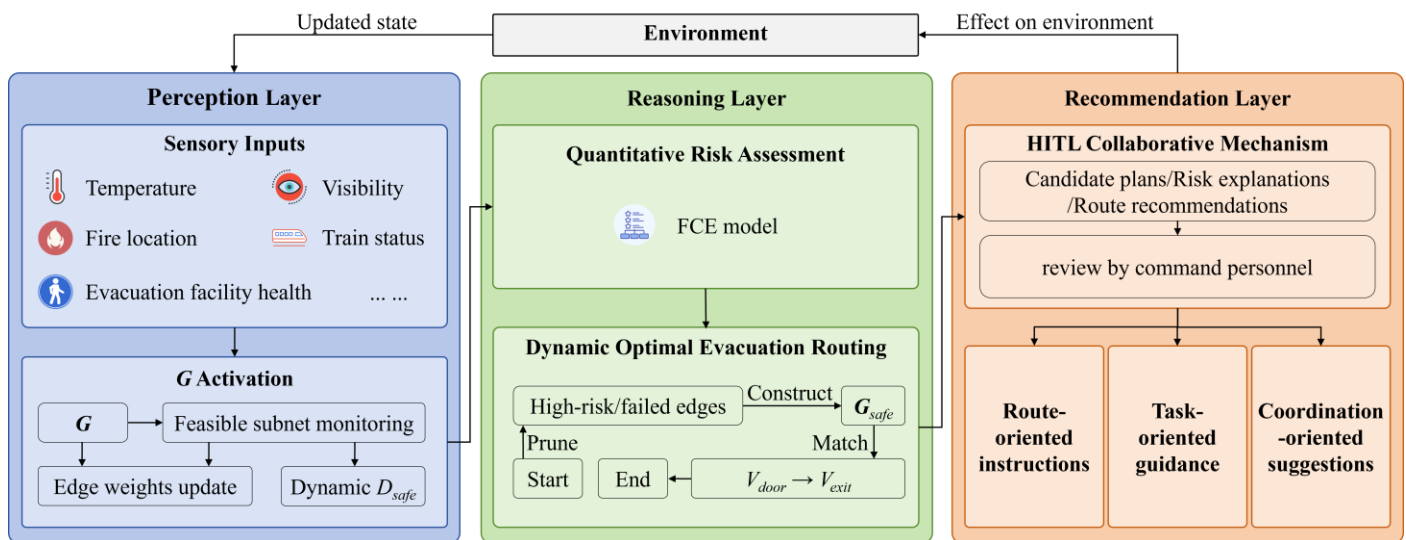


Figure 2. Architecture of the evacuation IDSS based on the PRR paradigm.

The reasoning layer constitutes the computational core of the evacuation IDSS. First, the FCE model is used to quantify the post-stop evacuation risk under the current fire scenario, and the dominant sources of risk among the hierarchical indicators are identified. It then uses the dynamic routing algorithm to update the available topological graph, exclude high-risk nodes and failed edges, construct the dynamically safe subgraph G_{safe} , and match each train-door node with a feasible safe exit that satisfies fire-avoidance, spatial accessibility, and passage capacity constraints. The reasoning layer further includes an LLM interface for structured input parsing, tool invocation, and recommendation organization. In the prototype, this interface used Qwen3.5 [55] as the LLM and invoked it through an API wrapped by LangChain [56]. The model was not fine-tuned. Domain adaptation was limited to prompt templates, tool schemas, and the BTCS fire evacuation knowledge base. The prompt specified the task scope, available tools, required fields, output format, and safety constraints. The FCE matrix and the dynamic topology optimization algorithm were implemented as Python (Version 3.12) callable tools and registered in the IDSS tool library. The LLM parsed structured scenario inputs, selected the required tools, passed standardized arguments, and organized the returned results into a reviewable recommendation package. It did not directly calculate the FCE safety scores or shortest paths. Raw engineering drawings were not interpreted during online interaction. Their geometric and functional information had been pre-encoded as structured topology and scenario parameters. Through this layer, the proposed IDSS couples quantitative risk assessment, topology-based route optimization, and LLM-assisted orchestration, thereby converting the evolving disaster state into computable and human-reviewable evacuation strategies.

The recommendation layer organizes the outputs of the reasoning layer into advisory information that can be reviewed, modified, and adopted by command personnel. Consistent with the decision-support nature of IDSS, the proposed system is positioned as a computational advisory module within a human-in-the-loop (HITL) framework [57], in which command personnel retain full decision authority. For each decision cycle, this layer presents a structured recommendation package as review evidence. Based on this evidence, command personnel can accept the recommendation, adjust the assigned routes, or reject the package and revert to the manual command chain. Any adopted instruction

is issued through the existing dispatching procedures rather than by the IDSS itself. The accepted or manually adjusted results are recorded in the decision logs, and the updated route and passage states enter the next perception cycle as structured inputs for recommendation update. However, these outputs are not executable control commands but serve only as structured decision-support information.

Overall, the proposed PRR-based architecture defines the functional boundary of the evacuation IDSS. The perception layer provides structured state inputs, the reasoning layer performs risk quantification and route optimization, and the recommendation layer translates computational results into human-reviewable emergency suggestions.

4.2. Operational Decision Logic of the Evacuation IDSS

Building on the PRR-based architecture, the operational logic of the evacuation IDSS consists of four sequential but iterative steps, namely, situational representation, local risk quantification, route assignment, and recommendation update. Through this process, the system can continuously update evacuation strategies as the fire environment, infrastructure availability, and crowd distribution evolve.

At the beginning of an incident, the IDSS interprets incoming alarm signals, monitoring data, and infrastructure-state information to construct a real-time situational representation of the BTCS fire scene. This representation can be formulated as a time-varying state vector S_t , as shown in Equation (16), where the subscript t denotes the current decision time step. Specifically, the hazard propagation state H_t captures the longitudinal location of the fire and the hazard propagation direction; the infrastructure availability F_t evaluates the operational conditions of exits and cross-passages and the overall bridge-tunnel safety status; and the local evacuee density P_t reflects the real-time crowd distribution.

$$S_t = (H_t, F_t, P_t)^T. \quad (16)$$

Based on the constructed situational representation, the IDSS decomposes the BTCS into multiple decision units $z \in Z$, such as train-door areas, passage segments, exit areas, tunnel-portal transition zones, and bridge sections, where z denotes the index of a decision unit, and Z denotes the set of all decision units. For each decision unit, the system invokes the risk assessment model to quantify the local evacuation risk index $R_z(t)$. Instead of producing only a global safety score, this formulation enables the IDSS to identify spatially heterogeneous risk constraints along different candidate evacuation routes. Within each specific unit z at time t , the normalized risk severity $r_{z,k}(t)$ quantifies the severity of the k -th risk factor from the comprehensive set K , encompassing fire proximity, visibility deterioration, structural unavailability, and local congestion risk. It is obtained by min-max normalization of the corresponding raw observation $\Phi_{z,k}(t)$ provided by the perception layer, as expressed in Equation (17):

$$r_{z,k}(t) = \frac{\Phi_{z,k}(t) - \Phi_k^{\min}}{\Phi_k^{\max} - \Phi_k^{\min}}, \quad \forall z \in Z, k \in K, \quad (17)$$

where $\Phi_k^{\min}$ and $\Phi_k^{\max}$ denote the lower and upper bounds of the k -th factor calibrated from engineering codes and on-site sensing thresholds. The corresponding weight w_k reflects the relative importance of each specific factor and is inherited from the indicator-layer weight vector A derived through the AHP-based expert survey procedure in Section 2.2, satisfying $\sum_{k \in K} w_k = 1$. The dominant local risk constraint is then determined by Equation (18).

$$R_z(t) = \max_{k \in K} \{w_k \cdot r_{z,k}(t)\}. \quad (18)$$

After local risk quantification, the IDSS activates the dynamic routing tool to assign evacuation directions for different passenger groups. Passengers located in different cars, different door areas, or different sides of the stopped train are treated as separate groups $g \in G$, where g denotes an evacuation group, and G denotes the set of all evacuation groups. For each group, the routing objective is to identify a feasible path that avoids fire-affected or rapidly deteriorating areas while maintaining reasonable proximity to available exits. Mathematically, the zone-aware routing objective is defined as the minimization of cumulative path risk exposure from the current time t to the expected evacuation completion time t_e , as expressed in Equation (19). Let $R_{path}(g, t)$ denote the instantaneous path risk exposure of evacuation group g at time t , which is obtained by aggregating the dominant local risk constraints $R_z(t)$ over all decision units z traversed by the candidate evacuation path of group g at that moment. Accordingly, the integral term represents the cumulative risk exposure accumulated along the evacuation path of group g throughout the evacuation process, and minimizing this term ensures that the assigned route maintains the lowest possible aggregate risk under evolving fire and infrastructure conditions.

$$\min \sum_{g \in G} \int_{t_0}^{t_e} R_{path}(g, t) dt . \quad (19)$$

During this process, the IDSS updates the safe topological subgraph G_{safe} according to the fire-source location, unavailable nodes, failed edges, and passage-capacity constraints. If several exits remain available, the system compares their path risk, expected congestion level, and accessibility conditions to avoid secondary crowding. If a previously feasible path becomes blocked or its risk exceeds the acceptable threshold, the affected passenger group is reassigned to an alternative route. Therefore, the output is not a one-time shortest-path result but a continuously updated set of coordinated route recommendations.

The cross-regional coordination mechanism is embedded in the above decision loop. Evacuation in BTCs usually involves several coupled spaces, including the train interior, tunnel section, portal transition zone, bridge segment, and adjacent safe areas. Therefore, the IDSS must coordinate not only passenger movement but also the operational relationships among guidance, broadcasting, lighting, ventilation, access control, and rescue-support subsystems. Once a route assignment is generated, the system further converts it into differentiated recommendations for the passengers, staff, and infrastructure subsystems, as summarized in Table 3. These recommendations are designed to support command personnel in organizing evacuation, maintaining route clarity, isolating hazardous zones, and coordinating rescue access.

Table 3. Differentiated recommendation outputs of the IDSS across multiple target layers.

Target Layer	Action Orientation	Specific Recommendations Generated by the IDSS
Passengers	Route-oriented	Dynamic directional guidance, carriage-specific broadcast messages, evacuation sequence prioritization
Staff	Task-oriented	Crowd organization instructions, limits for initial fire suppression, mandatory withdrawal alerts
Infrastructure subsystems	Coordination-oriented	Accident-zone isolation suggestions, emergency-lighting coordination, access-control suggestions for cross-passages, ventilation and smoke-exhaust coordination

During implementation, the IDSS continues to receive feedback from the field, including on passenger movement, environmental deterioration, passage occupancy, and facility-state changes. These feedback data are returned to the perception layer and used to update the situational representation S_i , the local risk index $R_z(t)$, and the available

subgraph G_{safe} . The system then performs a new round of risk quantification and route reassignment when necessary. In this way, the evacuation process is represented as a closed-loop decision-support chain rather than a fixed emergency procedure.

From a systems engineering perspective, the proposed IDSS transforms BTCS fire evacuation from a predefined emergency procedure into an adaptive socio-technical decision-support process. By coupling risk quantification, topology-based routing, cross-regional coordination, and knowledge-supported reasoning within a closed PRR loop, the system provides continuously updated and human-reviewable evacuation recommendations. This operational logic provides the basis for evaluating the IDSS's rapid route-generation and coordinated decision-support capability in the engineering case study.

The evacuation IDSS operates as an event- and interval-triggered advisory loop rather than a continuous, high-frequency controller. A new reasoning round is triggered either at a fixed re-evaluation interval or when a monitored state change exceeds a preset threshold, such as a confirmed shift in the fire-source position, the loss of an exit or cross-passage, or a pronounced change in measured temperature or visibility. Within each round, the structural topology remains fixed, and only node and edge availability are updated before the routing and risk assessment are re-solved on the pruned subgraph. Because the structural topology is reused and only the pruned subgraph is re-solved rather than the full model being rebuilt, the per-round update is designed to remain light relative to the evacuation timescale, so that the route recommendations can follow the sensed hazard state. The loop is reactive rather than predictive, since it updates routes based on the most recently sensed state and does not forecast the fire front's future position.

5. Engineering Case Study and Performance Evaluation

5.1. Engineering Scenario Construction

To verify the reliability and superiority of the proposed evacuation IDSS control framework under real extreme conditions, this paper adopts a single representative engineering case from an actual railway project in a mountainous plateau region of China, namely, the double-track railway BTCS shown in Figure 3. In contrast to single-track sections, evacuation in a double-track BTCS is constrained by the train body and the adjacent track. As a result, passengers can normally evacuate only through a safe-side single-sided passage, and bidirectional diversion is difficult to achieve. This structural characteristic makes the present case particularly suitable for validating the ability of the IDSS to perform single-sided evacuation, dynamic route reassignment, and cross-regional coordinated decision support under severely constrained conditions.

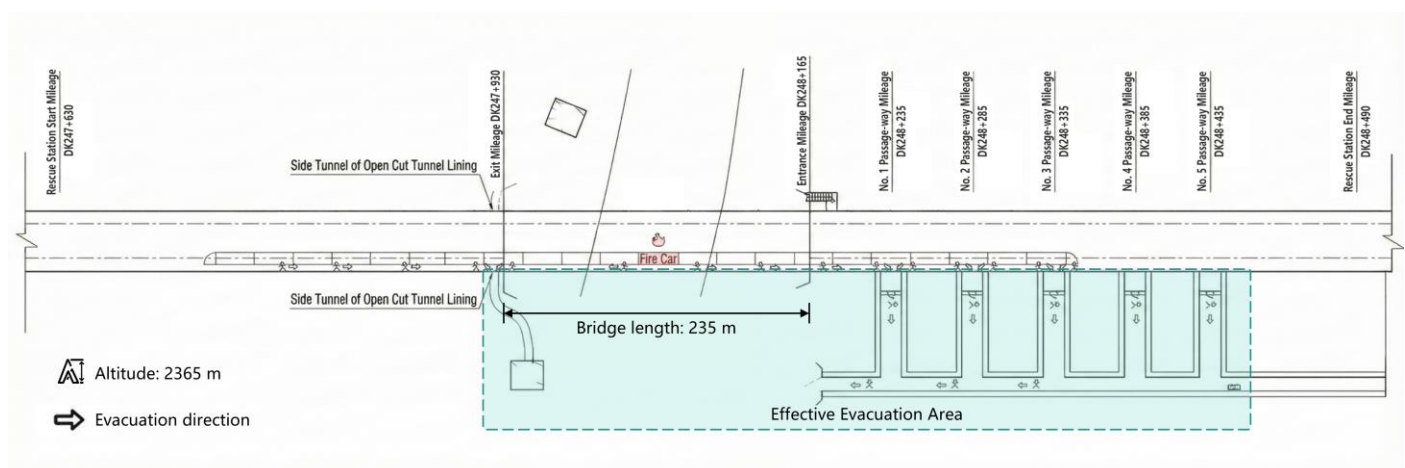


Figure 3. Distribution of evacuation exits in the double-track railway BTCS.

The double-track railway BTCS is located at an average altitude of approximately 2365 m. It is persistently exposed to a typical plateau environment characterized by severe cold and low atmospheric pressure. The bridge within this section has a total length of 235 m, with the two ends located at chainages DK247 + 930 and DK248 + 165. In accordance with the engineering scope defined for the present evacuation-routing analysis, a 1-km domain on both sides of the tunnel portals was considered. An asymmetric network of available safety exits is deployed in this scenario, including the left-side exits at DK247 + 930, DK248 + 235, DK248 + 285, DK248 + 335, DK248 + 385, and DK248 + 435. This configuration provides the topological basis for single-sided crowd diversion by the IDSS.

For the construction of the specific fire emergency scenario, it is assumed that a fully loaded CRH3A train traveling on the left-hand side catches fire while passing through the abovementioned railway BTCS. The fire source is assumed to be located in the middle of the fourth carriage, and at the initial stage, the fire poses a high risk of rapid thermal-radiation-driven spread to adjacent carriages. After the train's fire alarm system is activated, the driver immediately applies emergency braking. In the present double-track case, the center of the burning carriage eventually stops at chainage DK248+047 within the BTCS. By carefully defining the environmental constraints and geometric topological information, this engineering scenario provides a solid data foundation for the subsequent quantitative simulation and dynamic decision-making validation of the IDSS.

To support the quantitative risk assessment in this engineering case, a single-round structured expert survey was conducted between March and August 2025 to determine the AHP weight distribution and the rating-layer scores required by the FCE model. A panel of 30 senior experts was invited to participate, including railway tunnel design institutes, tunnel fire-safety research institutions, railway operations and emergency management departments, and evacuation engineering research teams, each with at least 10 years of relevant professional experience. The questionnaire consisted of two parts. The first part collected pairwise importance judgments for every level of the indicator hierarchy. It produced 11 pairwise-comparison matrices in total, namely 1 matrix at the target level, 3 matrices at the criterion level, and 7 matrices at the indicator level. The second part collected bottom-level indicator scores based on the five-grade 100-point criteria in Table 2, which were subsequently used to construct the FCE membership information. The CR verified the consistency of every pairwise-comparison matrix, and the maximum CRs at the target, criterion, and indicator levels were 0.032, 0.061, and 0.079, respectively, all below the 0.10 threshold. Of the 30 returned questionnaires, those that were incomplete or whose pairwise-comparison matrices did not reach a CR below 0.10 after expert feedback were treated as invalid and excluded, leaving 27 valid questionnaires for the final aggregation. The pairwise judgments collected from the valid questionnaires were first combined using the geometric mean, and the principal eigenvector of each aggregated matrix yielded the corresponding weight vector. The aggregated weight vectors at all levels of the hierarchy are presented in Figure 4 and constitute the static weight system that is embedded into the long-term memory of the IDSS.

5.2. Autonomous Decision Process of the Evacuation IDSS

Based on the engineering scenario defined above and the LLM interface described in Section 4.1, this section describes the case-specific decision process of the evacuation IDSS in a representative BTCS fire environment. The execution process followed the PRR architecture and used the structured topology, scenario parameters, fire-source coordinates, train-stopping information, and available exits for the double-track case. In this case, the structured input package included the track type, fire-source coordinates, train stopping chainage, train-door node set, evacuation-exit node set, passage accessibility, and facility state. The corresponding output package included the invoked tools, pruned nodes and

edges, safe subgraph G_{safe} , assigned exits, FCE-based safety scores, routing results, and coordination suggestions for passenger guidance, staff organization, emergency lighting, and accident-zone isolation. Combined with the specific data from this scenario, the core execution process is illustrated in Figure 5. Although human authorization is positioned at the end of this process, the intermediate risk assessment and routing steps are executed by the deterministic encapsulated tools rather than by open-ended LLM generation, and every tool invocation, pruning operation, and score calculation is preserved in the decision log. When reviewing the recommendation, command personnel therefore receive a traceable evidence chain, including the invoked tools, the pruned nodes, the safe subgraph, and the route-level safety scores with their risk-level interpretation, on the basis of which the recommendation can be authorized, adjusted, or rejected.



Figure 4. Multi-layer weight distribution of the multi-dimensional risk assessment indicators.

When a fire occurs, the sensors transmit structured environmental parameters and infrastructure-state information to the working memory of the IDSS. After these inputs are parsed, the IDSS first invokes the *Topology_Builder* tool. After receiving the track-type parameter of the double-track BTCS, this tool automatically suppresses the redundant nodes on the non-opening side through a masking mechanism. It activates only the available exits within the safe-side evacuation network, including the left-side exits at DK247 + 930, DK248 + 235, DK248 + 285, DK248 + 335, DK248 + 385, and DK248 + 435. In this way, the tool constructs a single-sided evacuation subnet. It completes the mathematical instantiation of the underlying spatial graph G , thereby providing the data foundation for the subsequent reasoning process.

Before generating the initial evacuation routes, the IDSS then triggers the core spatial-computation tool *Pruning_Tool*. When the algorithm detects that the physical distance between a target topological node and the fire-source center falls below the case-specific safety threshold D_{safe} , set to 25 m in this study, the IDSS's execution engine immediately returns a pruning instruction. This value is consistent with both the 25 m car body length of the CRH3A train set [58] and half of the 50 m spacing between adjacent evacuation exits in the selected rescue-station area, which is also 25 m. Under this constraint, the high-risk fire-affected nodes and their associated edges are penalized with infinite traversal weights, thereby causing the original global topological graph to collapse into a safe available subgraph, G_{safe} . For the valid nodes and candidate passages retained in G_{safe} , the IDSS further

invokes the *Risk_Assessment_Tool* to perform a quantitative safety reassessment. Specifically, the IDSS transforms the real-time extracted hazardous environmental variables into rating-layer indicators consistent with the multi-dimensional risk assessment framework and injects them into the FCE engine as a dynamic parameter matrix. The comprehensive quantitative score from the FCE matrix is then used to rank the risk levels of the candidate evacuation sections, thereby providing rigorous mathematical support for the next stage of global optimal route matching.

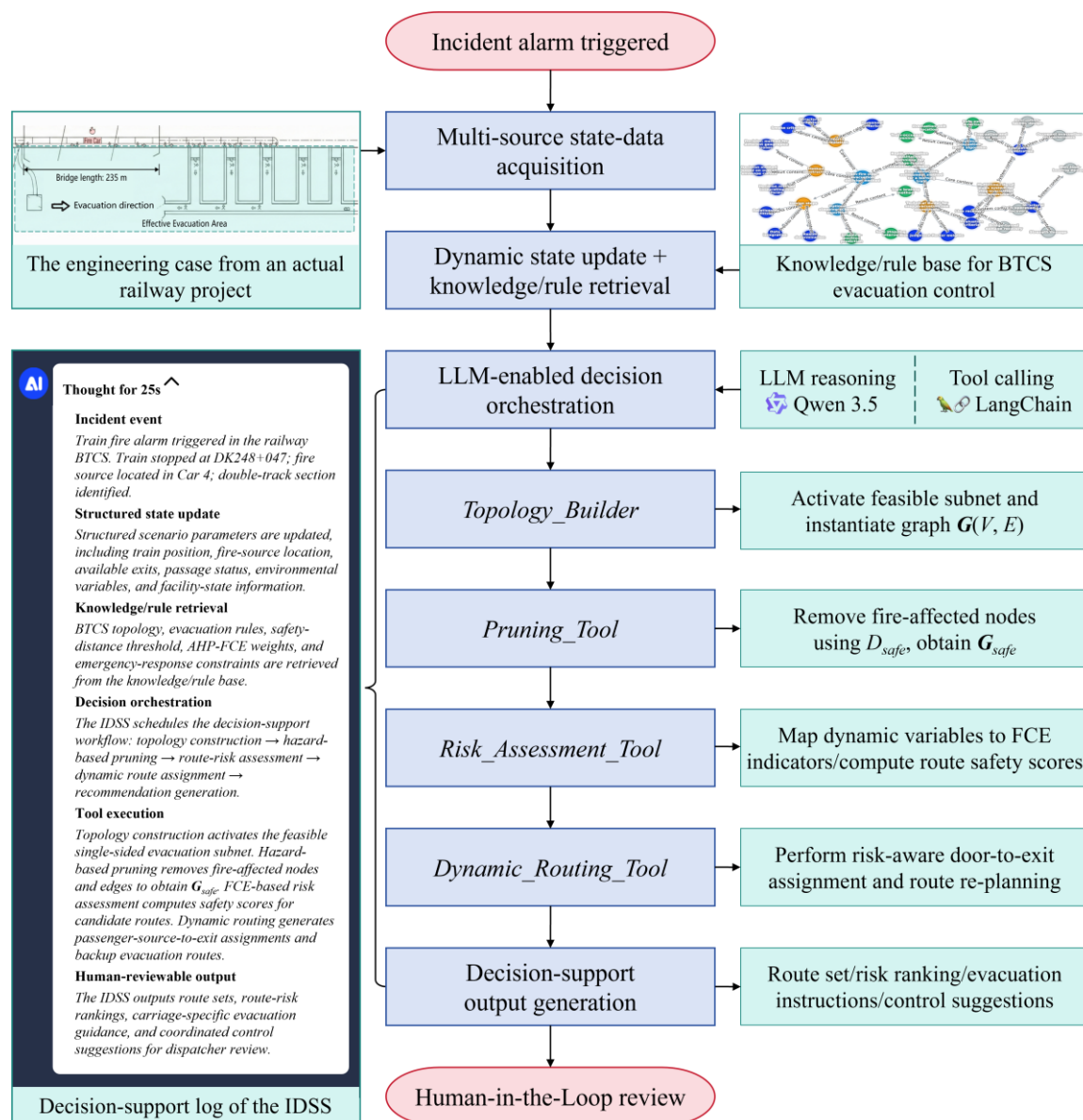


Figure 5. Autonomous decision-making process of the evacuation IDSS in representative BTCS fire scenarios.

Based on the updated safe subgraph G_{safe} , the IDSS continuously invokes the *Dynamic_Routing_Tool* to perform the final route allocation. At the algorithmic level, this tool uses the door nodes of each carriage as starting points and computes, in parallel, the minimum-weight paths to all available exits. At this stage, the optimization mechanism shifts to a strategy that relies more deeply on the integrated FCE score, preferentially matching evacuees to evacuation anchors with the lowest risk level and the most reliable environmental conditions. For example, under an emergency scenario involving rapid fire spread, if a passage that was originally the physically nearest route experiences a sharp decrease

in safety score because of smoke accumulation, the IDSS will immediately trigger route replanning through its internal reasoning process. In this way, it breaks the conventional static nearest-exit heuristic and adaptively redirects the affected passenger flow toward more distant but lower-risk redundant exits located at the front or rear ends of the line. After computation, the optimal safe node sequences generated by the IDSS are organized into cross-regional coordinated evacuation recommendations, including carriage-specific diversion suggestions, recommendations on route-specific emergency-lighting activation and guidance adjustment, and accident zone isolation suggestions. Finally, after review under the HITL mechanism, these recommendations may be adopted and implemented by command personnel through existing dispatch procedures.

5.3. Quantitative and Procedural Evaluation of the IDSS

5.3.1. Quantitative Safety Score Comparison Under Different Decision Modes

In this subsection, the evacuation risk across different decision modes for the double-track BTCS fire scenario is quantitatively compared. The overall post-stop evacuation safety scores under the conventional and IDSS decision modes are calculated to evaluate the effectiveness of the proposed framework. In this scenario, the fire is assumed to have spread significantly, with high-temperature thermal radiation and dense toxic smoke rapidly deteriorating the environment near the ignition point and severely compressing the available evacuation space. Notably, the present validation focuses on the two representative passages closest to the fire source, as they are the most sensitive to hazard propagation and passage capacity degradation; therefore, the dynamic hazard avoidance and route-replanning capabilities of the IDSS are tested.

Under the conventional decision mode, occupant evacuation relies entirely on fixed safety-exit signs on the tunnel walls and the instinctive tendency to escape via the nearest route. Because this mode lacks real-time hazard perception and dynamic route reconstruction capability, many passengers still evacuate along the initially planned shortest physical routes, inevitably passing through or being exposed to areas affected by high-risk thermal radiation, as illustrated by Routes 2 and 4 in Figure 6. This passive evacuation mode causes a rapid deterioration in the underlying indicator states, particularly leading to substantial score losses in critical indicators such as evacuation passage availability, crowd density, and total evacuation time. In contrast, under the IDSS decision mode, the perception layer of the IDSS immediately identifies that the physical environment along the corresponding passage has fallen below the safety threshold and instantly triggers the high-risk node pruning mechanism, forcibly removing the failed passage from the topological network. The dynamic routing algorithm subsequently breaks the conventional nearest-exit inertia and replans a redundant safe route for the affected passenger flow that is slightly longer in physical distance but completely avoids the core fire-affected area, as shown by Routes 1 and 3 in Figure 6. This adaptive intervention effectively improves crowd distribution and alleviates passage congestion as the fire approaches.

As shown in Figure 6, the upper part displays the simplified spatial topology of the BTCS, including the fire-affected area, the train doors, the available exits, and the four candidate routes, while the lower part presents the dialogue panel of the IDSS prototype. In this panel, command personnel submit structured queries, and the IDSS returns a reviewable recommendation package that includes the scenario summary, route definitions, compared decision modes, quantitative safety scores with their risk-level interpretations, the mechanism of the score differences, and the recommended primary and backup routes. Command personnel can trace each conclusion back to the corresponding tool outputs before authorizing, adjusting, or rejecting the recommendation.

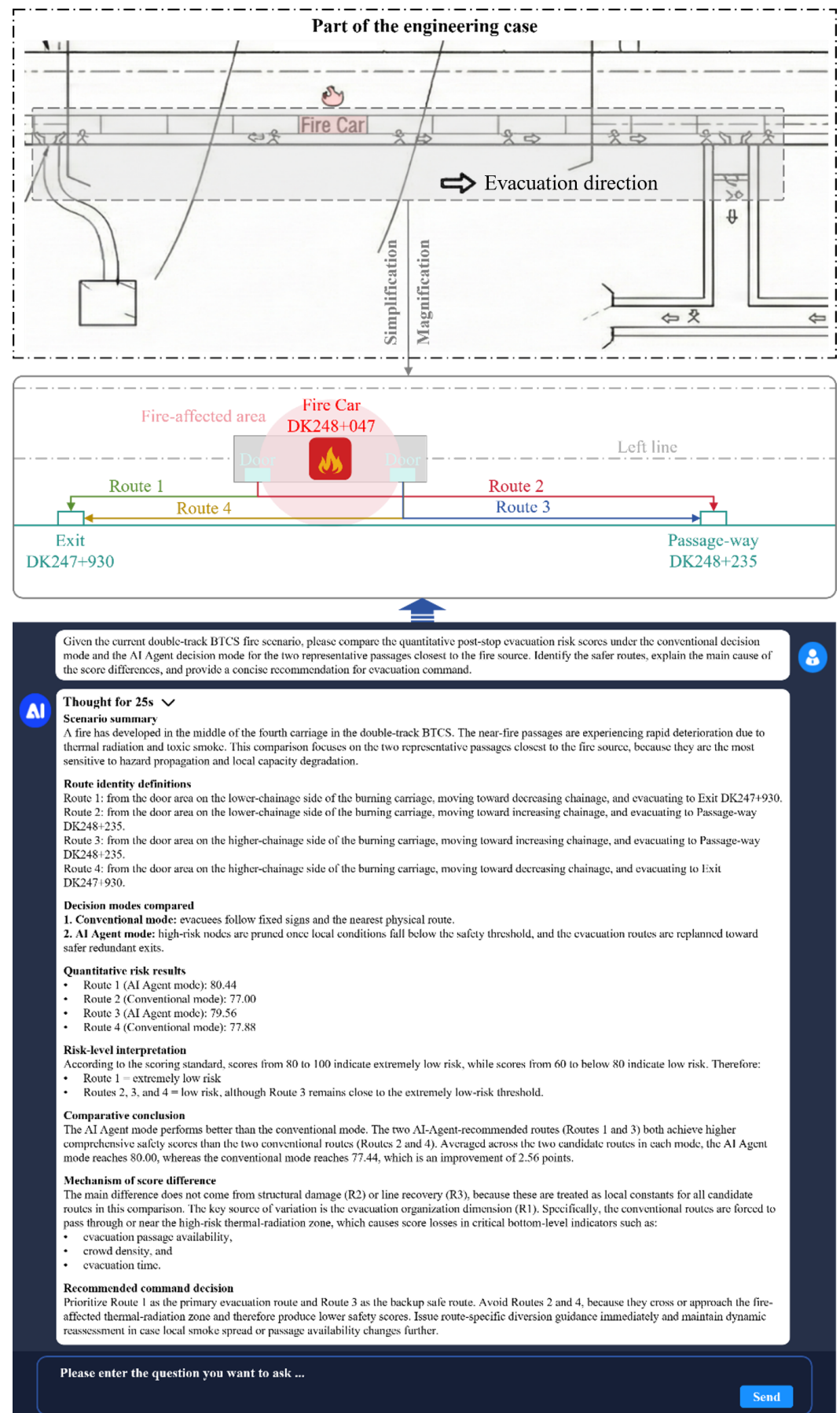


Figure 6. Spatial topologies of the four candidate routes and the IDSS interaction interface.

Within the local region affected by the train fire, the extent of infrastructure damage in terms of structural damage R_2 and line recovery R_3 may be regarded as a global constant for all the candidate routes. Therefore, the key mechanism determining the difference in safety risk among individual routes lies in the dynamic evolution of the evacuation organization dimension R_1 . The principal physical difference among the routes is whether the evacuation trajectory is forced to pass through or adjacent to the high-risk thermal radiation zone generated by the fire source.

During dynamic inference, the IDSS invokes its built-in *Risk_Assessment_Tool*. Based on the actual physical characteristics and hazard-coupled states of the four routes at the current moment, the perception engine of the IDSS derives the dynamic scores of the underlying indicators listed in Table 4. The IDSS then automatically executes the FCE algorithm, performing layer-by-layer dot-product calculations between the real-time indicator score matrix it generates and the expert weight vectors stored in long-term memory, thereby directly outputting the overall quantitative safety scores of the four routes (see Table 5).

Table 4. State scores of the underlying indicators for the four evacuation routes.

Route No.	1	2	3	4
Evacuation equipment	80	80	80	80
Evacuation passage	90	60	70	60
Evacuation exit	80	80	80	80
Evacuation plan	80	70	80	70
Disaster response	80	80	80	80
Evacuation mode	80	70	80	70
Crowd density	80	70	80	70
Group speed	80	70	80	70
Evacuation time	80	70	80	70
Line damage	80	80	80	80
Surface damage	80	80	80	80
Internal damage	80	80	80	80
Tunnel strength damage	80	80	80	80
Bridge strength damage	80	80	80	80
Structural damage recovery	80	80	80	80
Line damage recovery	80	80	80	80
Disaster organization management	80	80	80	80
Fire information integration	80	80	80	80

Table 5. Quantitative safety scores of the four potential evacuation routes.

Route No.	1	2	3	4
Evacuation safety score	80.44	77.00	79.56	77.88

The FCE and the routing algorithm are executed as precompiled Python tools invoked by the LLM, so the weighted aggregation that produces each safety score is deterministic. To verify the stability of the resulting decisions, the full IDSS pipeline was executed 10 times independently for this scenario. The comprehensive safety scores in Table 5 were reproduced identically across all 10 runs. In each run, the IDSS pruned the same fire-affected nodes and recommended the same fire-avoiding routes, resulting in a route-decision agreement rate of 100%.

Building on the route scores reported in Table 5, a one-at-a-time sensitivity analysis was performed to test the robustness of the assessment. Each criterion- and indicator-level weight was increased or decreased by 10%, followed by renormalization within its parent indicator. Since the four candidate routes differ only in the evacuation organization

dimension and have identical scores for structural damage and line recovery, their relative ranking remained unchanged across all perturbation scenarios. This result indicates that the evacuation organization indicators mainly determine the route ordering and remain insensitive to minor weight perturbations within the tested range.

Analysis of the above results indicates that Routes 2 and 4 under the conventional mode fail to avoid the high-temperature thermal-radiation zone. As a result, the usable space in the local passage is severely compressed, leading to sharp score reductions in critical bottom-level indicators, such as the number of evacuation passages R_{112} , crowd density R_{131} , and evacuation time R_{133} . The annular weight distribution further indicates that the indicators under the evacuation organization dimension R_1 occupy a dominant position with relatively high weights in the overall evaluation system. Therefore, once these core indicators suffer score losses under conditions of local congestion and fire exposure, the resulting penalties are progressively amplified through the hierarchical fuzzy matrix operations of the IDSS, ultimately determining the overall comprehensive safety level of each route.

The quantitative evaluation results in Table 5 show that Routes 1 and 3, which are automatically generated and recommended by the IDSS, achieve higher safety scores than Routes 2 and 4, which contain high-risk crossing segments. For example, Route 1 achieves a comprehensive safety score of 80.44, corresponding to an extremely low risk level. In contrast, Route 2, which guides evacuees through a thermal-radiation hazard zone, suffers severe score losses in the evacuation organization dimension and consequently drops to an overall score of 77.00, corresponding to a low risk level. This quantitative comparison, which is grounded in the underlying computational logic of the IDSS, mathematically confirms that the IDSS developed in this paper can autonomously and effectively avoid the core fire-affected zone. Organizing cross-regional evacuation with reference to its dynamically generated recommendations provides greater safety margins and stronger scientific validity.

Moreover, the evaluation results and computational paradigms also provide theoretical support for the macroscopic optimization of disaster prevention infrastructure in complex environments. Before formal operation, management agencies can use the IDSS framework to conduct full-sample static risk assessments of all physically connected candidate routes within a given section, thereby identifying primary and backup safe routes in advance. When a disaster occurs, the IDSS can further perform routine dynamic reassessments by incorporating real-time health monitoring data from onsite facilities. This mechanism effectively compensates for the shortcomings of purely shortest-path algorithms, which often lack global coordination capability when dealing with complex diversion scenarios involving dense exit distributions or large rescue stations; thus, it provides a solid foundation for intelligent evacuation management and control in extreme environments.

From a workflow perspective, the main advantage of the IDSS lies in shifting the command personnel's workload from manual route derivation to structured recommendation review. Under conventional dispatching, emergency managers must collect alarm information, retrieve emergency plans, judge route availability, and formulate evacuation guidance through separate serial steps. In the IDSS mode, risk assessment, topology pruning, and route allocation are automatically completed by the embedded computational toolchain, and the resulting evacuation routes, risk explanations, and coordination suggestions are presented as a reviewable recommendation package. Emergency managers can therefore focus on verifying the consistency of these recommendations with the onsite situation and operational rules before authorizing or adjusting them through existing dispatching procedures. This transformation does not replace human decision authority but

reduces repetitive information retrieval, route reconstruction, and preliminary risk comparison in the decision-support stage.

5.3.2. Engineering Review of IDSS Decision Outputs

In safety-critical transportation infrastructure, decision recommendations generated by LLM-enhanced IDSSs should be subjected to engineering review to reduce the risk of hallucinated reasoning, non-compliant suggestions, or operationally infeasible actions. Therefore, this subsection introduces a preliminary human-review protocol to assess the engineering rationality and operational compliance of the decision logs produced by the IDSS for the representative double-track BTCS fire case established above.

Considering the evacuation characteristics of the present double-track BTCS scenario, four review criteria were defined. The first is accuracy of environmental-context evaluation (AECE), which examines whether the IDSS can correctly interpret the structured situational inputs used in this paper, including the fire-source location, dominant smoke-spread direction, infrastructure-state information, and abnormal equipment states. The second is rationality of dynamic node pruning (RDNP), which evaluates whether the IDSS's identification and forced removal of high-risk nodes are consistent with the predefined safety-distance threshold and whether unsafe route continuity through the fire-affected zone is effectively avoided. The third is overall rationality of global route allocation (OGRA), which assesses whether the generated carriage-level evacuation routes avoid high-risk areas, reduce unnecessary route conflicts, and remain feasible under the single-sided evacuation constraints of the double-track BTCS. The fourth is compliance with cross-regional recommendations (CCRR), which evaluates whether the coordinated recommendations generated by the IDSS, including carriage-specific broadcasting, accident zone isolation, emergency lighting, and subsystem coordination, are consistent with the *Code for Design on Rescue Engineering for Disaster Prevention and Evacuation of Railway Tunnel* [59].

A 0–2 Likert scale [60] was adopted for expert scoring. A score of 2 indicates that the recommendation is accurate, feasible, and compliant with engineering practice; a score of 1 indicates that the recommendation is safe and executable but contains conservative redundancy, incomplete prioritization, or room for further refinement; and a score of 0 indicates that the recommendation involves logical errors, non-compliant operations, or evident safety hazards. Given the stochasticity of LLM-assisted recommendation generation, the same double-track BTCS fire scenario was evaluated across five independent runs, yielding five complete decision logs. A five-member expert panel with relevant backgrounds in tunnel fire safety, evacuation engineering, and emergency management reviewed these anonymized logs. Each review focused on the decision outputs and predefined criteria rather than on the internal generation process. Consequently, each evaluation criterion received 25 ratings. The average scores are summarized in Table 6, and the corresponding score distributions are shown in Figure 7.

Table 6. Average expert evaluation scores for the IDSS outputs in the case.

Evaluation Metrics	Evaluation Scores
AECE	1.92
RDNP	1.88
OGRA	1.84
CCRR	1.76

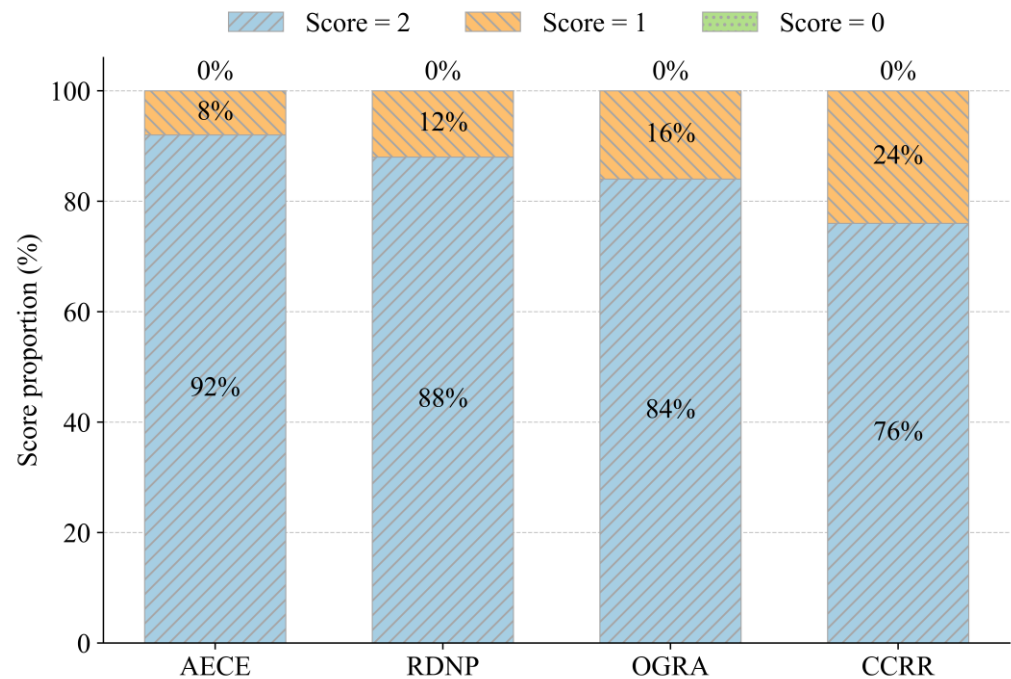


Figure 7. Distribution of expert evaluation scores for the four engineering criteria.

The review results indicate that the IDSS decision outputs were generally determined to be feasible and compliant under the representative double-track BTCs fire scenario. No score of 0 appeared in the repeated evaluations, indicating that no output contained explicit safety violations, non-compliant operations, or unacceptable engineering errors. Among the four criteria, AECE achieved the highest average score of 1.92/2.00, suggesting that the IDSS could consistently interpret the structured environmental and infrastructure-state inputs used in the case. RDNP also obtained a high score of 1.88/2.00, indicating that the IDSS could stably enforce the safety distance constraint and remove fire-affected nodes without generating unsafe route continuity.

The OGRA score reached 1.84/2.00, indicating that the IDSS-generated route allocations were generally reasonable under the single-sided evacuation constraints of the double-track BTCs. This result should be interpreted as an engineering rationality assessment under the current topology–risk evaluation framework rather than as proof of mathematical global optimality in a full multi-objective evacuation-optimization sense. By comparison, the CCRR obtained the lowest average score of 1.76/2.00, although it remained within the favorable range. These results suggest that compared with structured information interpretation or topological pruning, cross-regional recommendation generation is more context sensitive. In several repeated runs, the IDSS tended to generate conservative but executable coordination suggestions, particularly regarding the sequencing of carriage-specific broadcasting, regional isolation, and subsystem linkage. These suggestions were judged to be operationally acceptable, although some outputs showed conservative redundancy in the sequence of broadcasting, regional isolation, and subsystem coordination.

To make the basis of the CCRR criterion explicit, each recommendation category in Table 3 was checked item by item against the functional requirements of the disaster-prevention code [59]. The directional guidance and topological pruning outputs map to the requirements on evacuation routes, evacuation walkways, and cross-passage spacing, because the safety-distance threshold and the candidate topology are pre-encoded from a design that already satisfies these requirements. The accident-zone isolation and cross-passage access-control suggestions map to the requirements on hazard separation and controlled passage use. The emergency-lighting coordination maps to the requirements

on emergency lighting and evacuation indication. The ventilation and smoke-exhaust coordination maps align with the requirements for smoke control during evacuation. The carriage-specific broadcasting maps to the requirements on evacuation guidance and emergency announcement. Across the five repeated runs, no recommendation contradicted these functional requirements, consistent with the absence of any zero scores for the CCRR criterion.

The scope of this compliance assessment should also be clarified. The mandatory provisions of these codes are design-stage requirements on infrastructure geometry, equipment, and illuminance that are already embedded in the pre-encoded topology and safety thresholds, whereas the IDSS outputs remain advisory and are ultimately applied by command personnel through existing dispatching procedures. At the decision-support level, the review confirms that the recommendations are functionally consistent with the disaster-prevention code, while their formal certification against the mandatory provisions of the fire safety codes and dispatching rules is carried out during commissioning and regulatory review.

Overall, the human evaluation results support the engineering rationality and operational feasibility of the proposed IDSS in a representative double-track BTCS fire scenario. Combined with the quantitative safety score comparison and the qualitative procedural discussion above, the human evaluation results further indicate that the IDSS can serve as a decision-support module for evacuation management under strongly constrained railway fire conditions. This workflow-level advantage is reflected mainly in the reduction in manual information retrieval, route reconstruction, preliminary risk comparison, and recommendation organization before human authorization. Therefore, the proposed IDSS does not replace the established command chain but provides a structured decision-support basis for more consistent and timely evacuation management under constrained railway fire conditions.

5.4. Discussion

Although the proposed evacuation IDSS provides a computable framework for risk assessment, dynamic route generation, and engineering recommendations in BTCS fire scenarios, several limitations remain. First, the current dynamic routing algorithm identifies fire-affected nodes through a predefined safety distance threshold rather than a physically computed tenability boundary. A more rigorous D_{safe} should be derived from the dynamic tenability boundary of the fire field, which depends on thermal radiation, gas temperature, toxic gas concentration, and visibility, together with ventilation, train stopping position, and environmental constraints. The framework also assumes that the perception inputs, including the estimated fire-source position, are timely and accurate. In practice, however, they may be incomplete, delayed, or unreliable, and the system updates routes reactively rather than forecasting the fire front. The decision cycle, sensor sampling frequency, and per-round computation time are not field-measured in the present case study. Future work should embed lightweight fire-dynamics prediction models or fire digital twins into the perception layer so that hazard boundaries and safety thresholds can be updated and anticipated as the fire evolves, quantify the decision-cycle timing through controlled drills and operator-in-the-loop testing, and add mechanisms for handling degraded sensing in real-world conditions.

Second, the present route optimization model is intentionally formulated at the macroscopic level, representing passage capacity and local congestion via topological constraints and weight penalties, so that route reassignment remains a lightweight graph search within the online decision loop. At this level, exit capacity enters only as a topological feasibility constraint, and the door-to-exit assignment follows the nearest-exit principle rather than a hard capacity-constrained optimal assignment. It therefore does not

resolve individual movement and cannot fully capture the heterogeneous walking speeds of mobility-impaired passengers, panic-induced behavior, congestion backflow, the effect of train-door opening sequences on the initial carriage outflow, the saturation of an exit when several doors are matched to it, or local bottleneck formation in narrow BTCS evacuation spaces. Microscopic models such as the social force and cellular automaton models can reproduce these effects but require fine-grained individual inputs and heavier computation, which limits their direct embedding in a real-time command loop. Future studies should therefore couple the IDSS with such models offline to calibrate local passage capacity and door-release sequencing and to introduce a capacity-constrained assignment that diverts surplus demand to the next-nearest feasible exit, while retaining the macroscopic model for real-time route reassignment, supporting more realistic congestion prediction and more refined batch diversion.

Third, the present quantitative validation is conducted within a single representative double-track BTCS scenario, in which the IDSS decisions are fully reproducible across repeated runs. However, the safety advantage over the conventional mode is established only for this configuration. Future work should conduct multi-scenario validation under different fire-source locations, train stopping positions, passenger densities, single-track and double-track structures, and ventilation conditions, and assess the statistical significance of the safety advantage across these scenarios. In addition, adoption-rate and manual-modification statistics require real drills or field operations, which are not yet available for the studied BTCS, and the current feedback loop only records accepted or adjusted decisions without learning from human corrections. Future work should obtain these statistics through controlled drills and operator-in-the-loop testing and develop a closed feedback mechanism that incorporates human corrections into the IDSS knowledge base. A clause-by-clause certification of each recommendation category against the mandatory provisions of the applicable fire safety codes and dispatching rules should likewise be obtained through the same controlled drills and field operations before operational use.

Fourth, abnormal LLM output is partly mitigated because the core risk and routing results are produced by deterministic encapsulated tools rather than the LLM, and the engineering review within the HITL setting allows command personnel to override implausible or non-compliant recommendations. For sensor failure or degraded data quality, the perception layer flags missing or out-of-range inputs, and the IDSS falls back to the predefined primary and backup routes from the offline full-sample static assessment rather than computing risk from corrupted data. For communication interruption, real-time situational updates are suspended, and emergency management continues through the manual command chain based on the last valid recommendation, since the IDSS provides decision support rather than executable control commands. A full quantitative failure mode and effects analysis, together with hardware and software redundancy for the sensing and communication subsystems, remains future work that requires field deployment and drill data.

6. Conclusions

To address the complex spatial coupling and extreme environmental constraints associated with occupant evacuation during train fires in railway BTCSs, this paper proposes an IDSS-driven decision-support framework for dynamic evacuation route planning and quantitative risk assessment. Based on validation using a real engineering case, the main conclusions are as follows:

- (1) A multi-dimensional risk assessment model for post-stop evacuation in railway BTCSs was established. By combining the AHP and the FCE method, the extreme environment and spatial constraints of BTCSs were translated into a quantitative evaluation framework encompassing evacuation organization, structural damage,

and line recovery. It helps address the limitations of conventional static assessment and provides a reliable computational basis for risk quantification and route allocation during fire emergencies.

- (2) A topology-adaptive algorithm for optimizing evacuation routes under dynamic fire constraints was developed. By integrating an improved nearest-exit principle with a dynamic high-risk node elimination mechanism, the algorithm reconstructs the safe connected subgraph based on the fire-source location and matches passenger flows from different carriages to redundant safe exits, thereby reducing the fire-exposure risk caused by local passage blockages.
- (3) An LLM-based orchestration interface was integrated into the closed PRR architecture of the evacuation IDSS. The risk quantification matrix and the dynamic routing algorithm are encapsulated as deterministic callable tools, while the LLM interface parses structured inputs, invokes these tools, and organizes the returned results into reviewable recommendations. Through this coupling, the system provides unified decision support for HITL emergency management in complex constrained spaces.
- (4) The engineering case study verifies the framework's reliability and effectiveness. In the representative double-track BTCS scenario, the IDSS-recommended routes achieved higher comprehensive safety scores than the conventional nearest-exit mode and remained fully reproducible across repeated runs. The expert review confirmed that the outputs were engineering-rational and operationally compliant, while procedural analysis indicated that the unified IDSS loop can reduce manual plan retrieval, route reconstruction, and preliminary risk comparison before human authorization, thereby supporting more consistent and timely evacuation management under constrained railway fire conditions.

Despite these results, the current framework still has several limitations. It identifies fire-affected nodes through a predefined safety distance threshold, represents crowd movement only at the macroscopic topological level, and has been validated only on a single double-track plateau scenario with single-sided evacuation, without field drills. The model and architecture are built on generic, structured topologies, so they can, in principle, be extended to other bridge–tunnel layouts and operating environments, although this broader applicability has not yet been quantitatively verified.

Future work will embed lightweight fire-dynamics prediction models or fire digital twins into the perception layer, couple the routing model with microscopic evacuation models, conduct multi-scenario validation under varied fire conditions, and verify operational reliability through controlled drills, operator-in-the-loop testing, quantitative failure mode analysis, and clause-by-clause code-compliance certification before operational use.

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was used as the embedded large language model to support natural-language interaction, structured decision-support explanation, and recommendation generation. The model outputs were reviewed and constrained by the authors based on predefined engineering rules and quantitative assessment results. The authors take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Abbreviations

The following abbreviations are used in our paper.

BTCS	Bridge–tunnel connection section
IDSS	Intelligent decision-support system
AHP	Analytic hierarchy process
FCE	Fuzzy comprehensive evaluation
LLM	Large language model
PRR	Perception–reasoning–recommendation
HITL	Human-in-the-loop
AECE	Accuracy of environmental-context evaluation
RDNP	Rationality of dynamic node pruning
OGRA	Overall rationality of global route allocation
CCRR	Compliance with cross-regional recommendations

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