

Article

Integrating Heterogeneous Stakeholder Interests into Resilience Optimization of Socio-Technical Infrastructure Systems: A Gain-Oriented Perspective Using Fuzzy-Evidential Bayesian Network

Zirui Li ¹, Guangchong Chen ², Shiqi Chen ¹, Guangyao Chen ¹ , Fenghua Tian ¹ and Qiming Li ^{1,*}

¹ Department of Construction and Real Estate, Southeast University, Nanjing 211189, China

² Department of Management Science and Engineering, Shanghai University, Shanghai 200444, China

* Correspondence: 101001839@seu.edu.cn

Abstract

Escalating threats from natural disasters and technical failures underscore the critical role of infrastructure resilience in sustaining operations and reducing losses. Existing studies have advanced resilience optimization, but still provide limited explanation of how resilience improvements are converted into stakeholder-specific gains or how such heterogeneous gains can guide strategy prioritization. This study aims to develop a gain-oriented infrastructure resilience optimization framework that explicitly links resilience strategies, resilience increments, stakeholder-specific gains, stakeholder groups, and aggregated system-level benefits. The framework is operationalized through a fuzzy-evidential Bayesian Network (FEBN) parameterized by triangular fuzzy numbers, Dempster–Shafer evidence theory, and Noisy-Or model, complemented by Dynamic Bayesian Network (DBN) analysis to simulate long-term optimization dynamics. A case study of Nanjing Metro Line 7 demonstrates the framework’s applicability. The results show that proactive strategies, particularly component reliability design (RS 1-1) and emergency response planning (RS 4-1), are high-leverage interventions for improving aggregated gain. Failure-scenario, parameter-perturbation, and baseline-comparison analyses indicate that the main prioritization results remain broadly stable under uncertainty and consistent with non-evidence BN baselines. The DBN results further reveal that operator-centered optimization improves aggregated gain over time but may produce asymmetric benefits. Overall, the framework supports transparent, stakeholder-oriented resilience strategy prioritization in socio-technical infrastructure systems.

Keywords: infrastructure system; resilience optimization; stakeholder interests; resilience strategy; Bayesian Network



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1. Introduction

Infrastructure constitutes the operational backbone of modern cities, sustaining mobility, public services, and economic activities [1]. However, increasing exposure to natural hazards, technical failures, cyber–physical disruptions, and cascading service interruptions has shifted infrastructure planning and management beyond traditional reliability- and safety-oriented paradigms toward resilience thinking [2,3], as echoed in the Principles for Resilient Infrastructure issued by the United Nations Office for Disaster Risk Reduction (UNDRR) [4]. Resilience emphasizes a system’s capacity to withstand, adapt to, and recover from disruptions across

the disturbance lifecycle. Extensive studies have advanced infrastructure resilience modeling, assessment, and optimization across transportation, power, port, and other critical systems [5–8], using methods such as genetic algorithms (GA) [9], Dynamic Bayesian Network (DBN) [5], and Reinforcement Learning (RL) [10]. While these studies have improved the identification of vulnerable components, performance degradation, and intervention priorities, most optimization models still treat resilience primarily as a technical or performance-oriented target [2]. They therefore provide limited explanation of how resilience improvements are translated into broader benefits that inform decision-making.

The socio-technical nature of infrastructure systems makes this gap especially important [2]. Resilience is not generated by technical components alone; it depends on coordinated resource allocation, including equipment investment, human input, emergency capacity, organizational coordination, and financial support [11]. These resources are controlled, provided, or affected by multiple stakeholders. In practice, decision-makers must determine which resilience strategies should be prioritized under limited resources, yet technical performance indicators alone do not fully explain who benefits from such strategies or what practical value they create. For example, fewer service interruptions may be most relevant to operators [12], reduced delays may be most visible to passengers [5], and improved emergency response may be closely associated with public agencies. Without explicitly representing such heterogeneous interests, resilience optimization may remain technically rational but practically incomplete.

Recent studies have shifted beyond performance-oriented resilience optimization toward value- or benefit-oriented perspectives [13–18], reframing resilience as a source of tangible benefits that can justify investment and guide strategy prioritization. For instance, existing research has quantified the economic return of typhoon-resilient housing [15], the resilience dividends of flood-control investments [16], and the lifecycle benefits of disaster-prevention infrastructure [18]. However, these efforts remain largely focused on aggregate system-level or economic benefits. A critical gap therefore remains: existing infrastructure resilience optimization lacks an explicit mechanism for integrating heterogeneous stakeholder interests and translating them into strategy prioritization. As a result, current models provide limited explanation of who benefits from resilience improvements, what tangible benefits are produced, and how such benefits should guide resource allocation.

Accordingly, this study develops a gain-oriented infrastructure resilience optimization framework that integrates heterogeneous stakeholder interests into strategy prioritization. Specifically, it aims to clarify how resilience strategies generate resilience increments, how these increments lead to stakeholder-specific gains, and how such gains inform strategy prioritization and long-term resource allocation. The concept of resilience gain proposed by UNDRR [4] is introduced and conceptualized as the tangible benefits generated by resilience improvement. By linking resilience strategies, resilience increments, resilience gains, stakeholder groups, and aggregated gain, this study reframes resilience optimization as a stakeholder-informed decision process. A fuzzy-evidential Bayesian Network (FEBN) is developed to model the uncertain and hierarchical process of gain generation. Static FEBN analysis is used to prioritize strategies, test robustness, and identify critical causal chains, while Dynamic Bayesian Network (DBN) analysis captures long-term optimization dynamics under resource constraints. The framework is demonstrated using Nanjing Metro Line 7, a Grade of Automation 4 (GoA4) urban metro system.

The contributions of this study are threefold. First, it introduces resilience gain as a conceptual bridge between resilience increments and stakeholder-specific benefits, extending resilience optimization from performance improvement toward stakeholder-centered value creation. Second, it develops an FEBN- and DBN-based analytical framework to model gain-generation pathways, identify high-leverage strategies, test robustness, and simulate long-term optimization dynamics under resource constraints. Third, it applies the framework

to a GoA4-level UMS, offering empirical insights and practical guidance for stakeholder-oriented resilience resource allocation in complex socio-technical infrastructure systems.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical background on infrastructure resilience, stakeholder interests, and the empirical context of GoA4-level UMS. Section 3 presents the FEBN- and DBN-based methodology. Section 4 reports the case study and analytical results. Section 5 discusses the theoretical and practical implications and limitations. Section 6 concludes the paper.

2. Theoretical Background and Literature Review

This section reviews the theoretical foundations and empirical context that underpin the study. Specifically, Section 2.1 reviews infrastructure resilience, Section 2.2 discusses stakeholder interests in resilience, Section 2.3 introduces the empirical context of UMS resilience management, and Section 2.4 synthesizes the research gap and objectives.

2.1. Resilience of Infrastructure Systems

Originating in the ecological domain, resilience was first proposed by Holling [3] as the capacity of systems to withstand disturbances, adapt to change, recover swiftly, and maintain core functions. Since then, this concept has been widely applied to various infrastructure systems, such as metro [5], railways [6], and ports [8]. Existing infrastructure resilience research has developed mainly from four perspectives [2,6,8]: First, the capability-based perspective conceptualizes resilience as a set of system capacities, such as absorptive, resistant, restorative, and adaptive capacities, which manifest across different disruption stages [2,5]. Second, the property-based perspective emphasizes resilience attributes, particularly the 4Rs framework of robustness, redundancy, resourcefulness, and rapidity [19], which has been extended in different contexts by incorporating attributes such as protectiveness, visibility, agility, and flexibility [1,6]. Third, the performance-based perspective quantifies resilience using performance-time curves, such as the resilience triangle, to capture functionality loss and recovery after disruptions [20]. Fourth, the socio-technical perspective views infrastructure as a complex system shaped by interactions among physical assets, operators, users, and governing organizations [8]. Frameworks such as TOSE further decompose resilience into technical, organizational, social, and economic dimensions, thereby extending resilience analysis beyond physical performance alone [2].

These perspectives provide the foundation for infrastructure resilience assessment and optimization. In resilience assessment, qualitative approaches, such as multi-criteria decision-making methods (e.g., AHP, TOPSIS, and SEM) [2], are commonly used to integrate expert knowledge, while quantitative approaches rely on measurable performance indicators and analytical models, including topology-based analysis (e.g., complex networks [21] and BN [5]), stochastic simulation (e.g., Monte Carlo analysis [22]), and data-driven paradigms such as Long Short-Term Memory (LSTM) networks [23]. Building on assessment results, resilience optimization seeks to identify effective intervention strategies across the disruption lifecycle, including preventative strategies (e.g., pre-allocation of protective facilities against hazards [17]), reactive response strategies (e.g., dynamic emergency protocols [21] or resource deployment [9]), and restorative strategies (e.g., enhancing post-disaster recovery efficiency [10]). Existing optimization studies have employed methods such as genetic algorithms [9], DBN [5], and reinforcement learning (RL) [10] to support resource allocation and sequential decision-making under constraints. However, these studies still mainly focus on improving system capacities, properties, or performance indicators, with limited attention to how such improvements are translated into stakeholder-specific benefits. This limitation motivates a gain-oriented perspective that connects resilience enhancement with the heterogeneous interests of infrastructure stakeholders.

2.2. Stakeholder Interests in Infrastructure Resilience

As discussed in Section 2.1, existing research on infrastructure resilience has advanced a multidimensional basis for modeling, assessment, and optimization, with a predominant emphasis on a system performance-centric paradigm. Such a view conceptualizes resilience as an intrinsic system property and prioritizes the enhancement of measurable resilience performance indicators [2]. However, the practical establishment and optimization of resilience inherently depend on diverse resources [11], necessitating substantial financial investments, technical equipment, and human capital. In this context, a critical yet often overlooked issue arises: what tangible benefits can stakeholders, particularly decision-makers governing resource allocation and investment, reasonably expect from system resilience? More importantly, how can stakeholder interests be systematically integrated into resilience-related decision-making?

This issue becomes particularly salient given that key decision-makers, such as infrastructure operators, often face remarkable resource constraints. Under such conditions, conceptualizing resilience merely as a technical indicator of safety and reliability is insufficient. Consequently, a shift toward value- or benefit-oriented perspectives has emerged, reframing resilience as a source of tangible benefits aligned with stakeholder interests [13–18]. This approach seeks to inform decision-making by quantifying resilience-induced benefits and assessing the cost-effectiveness of interventions [15,18]. Table 1 summarizes key studies exploring the economic, functional, and operational benefits of infrastructure resilience. Despite these advancements, current methods still face a notable limitation: resilience benefits are often assessed at an aggregate system level, without considering the heterogeneity of stakeholder interests. Different stakeholders may prioritize varying aspects of resilience; for example, metro operators may prioritize service continuity and operational efficiency [12], while passengers may value safety, punctuality, and comfort [5].

Table 1. Explorations in assessing resilience benefits or value.

Infrastructure Type	Disturbance	Assessment Approach	Objective	Ref.
Power grid	Natural disasters	Customer damage function	Quantify resilience value in reducing lifecycle energy costs	[13]
Community	Natural disasters	Cost–benefit analysis	Assess cost-effectiveness of community resilience measures	[14]
Urban housing	Typhoon	Cost–benefit analysis	Evaluate economic return of typhoon-resilient housing investment	[15]
Urban region	Natural disasters	Computable General Equilibrium model	Estimate resilience dividends from flood control investments	[16]
Urban region	Multiple disasters	Service replacement cost method	Quantify the preventive benefits of urban underground infrastructure	[17]
Urban region	Flooding	Lifecycle cost analysis	Quantify resilience benefits of urban flood control programs	[18]

In response, the present study introduces a novel concept of “resilience gain”, based on the *principles of resilient infrastructure* proposed by the United Nations Office for Disaster Risk Reduction (UNDRR) [4]. This concept emphasizes that investments in resilience interventions should yield positive, stakeholder-specific benefits, while acknowledging the inherent heterogeneity of stakeholder interests: different groups may prioritize safety, continuity, cost reduction, or social value to varying degrees [24]. In this study, resilience gain is operationalized as the expected benefits delivered to stakeholders through resilience

improvement, characterizing an explicit link between resilience strategies, performance improvements, and tangible outcomes aligned with stakeholder interests.

2.3. Resilience Management of UMS Operating at GoA4: An Empirical Context

This study is empirically grounded in the resilience management of urban metro systems (UMS), recognizing it as a vital component of urban lifeline infrastructure that delivers high-capacity public transportation essential to the sustainable functioning of modern cities [5]. Moving beyond the traditional scope of UMS resilience research on disasters such as fires [5] and floods [25], this study shifts attention to the resilience management of UMS operating at the latest Grade of Automation 4 (GoA4). By leveraging GoA4 automation, this type of UMS can further reduce minimum headways, improve service punctuality, lower operation costs, and minimize the impact of human error [26]. As such, GoA4-level UMS is increasingly regarded as the mainstream direction of UMS development, consistent with the broader trend toward intelligent urban infrastructure. This trend is evidenced by the recent rapid expansion of such lines in China (see Figure 1).

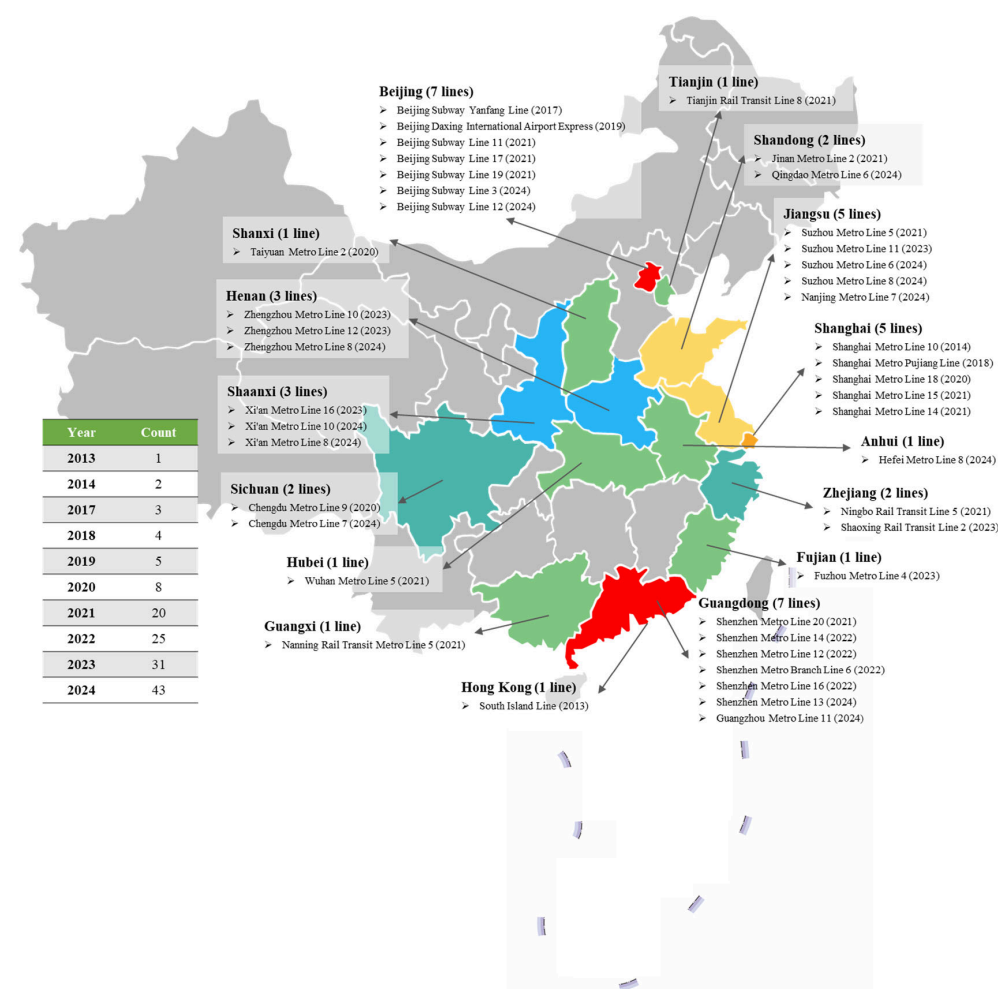


Figure 1. Statistics on GoA4-level UMS lines in China by 2024 (compiled by the authors based on publicly available data from the China Association of Metros, URL: <https://www.camet.org.cn/>, accessed on 26 May 2026).

Recent scholarship has examined the operation management of GoA4-level UMS from multiple perspectives, covering driver trust [27], safety performance [28], passenger satisfaction [29], and acceptance [30]. Technical challenges, such as uncertain wireless transmissions and cyberattacks [31], have also been investigated, contributing to a still-developing body of knowledge. Compared with traditional UMS, GoA4-level UMS features a higher degree

of subsystem coupling and functional interdependence [32]. This characteristic increases vulnerability to cascading disruptions triggered by localized failures, such as equipment breakdowns, power outages, or cyber intrusions, that may escalate into large-scale failures or systemic breakdowns [22], threatening operational continuity and system safety.

To mitigate these risks, recent studies have explored reliable control under cyber-attacks [33], triple-modular-redundant system [34], online safety monitoring [26], and accident causality analysis [35]. Although these approaches contribute to system safety, most remain reactive, focusing primarily on post-incident response rather than proactive mitigation. Given the uncertainty and sudden onset of disruptions in GoA4-level UMS, reactive measures alone are inadequate. In this context, system resilience, emphasizing proactive prevention, adaptive response, and rapid recovery, offers a more promising solution [2,5]. However, resilience-oriented management for GoA4-level UMS remains largely underexplored, and existing UMS resilience models offer limited guidance, as higher levels of automation and functional interdependencies further amplify system vulnerability.

2.4. Research Gap and Objectives

The preceding review reveals a critical research gap: existing infrastructure resilience optimization studies have not sufficiently explained how resilience improvements are translated into stakeholder-specific gains and used to prioritize strategies. Although recent studies have linked resilience enhancement with measurable outcomes, these outcomes are often assessed at the aggregate system or economic level, with limited attention to who benefits from resilience interventions and what benefits are generated. Consequently, existing models can identify technically effective interventions, but provide limited support for comparing alternative strategies and guiding strategy prioritization based on heterogeneous stakeholder interests.

To address this gap, this study develops a gain-oriented infrastructure resilience optimization framework that integrates heterogeneous stakeholder interests into strategy prioritization. As shown in Figure 2, the framework is organized around three objectives: (1) to introduce the concept of resilience gain for conceptualizing the tangible benefits generated by resilience enhancement and linking them to stakeholder interests; (2) to capture the linkage among resilience strategies, resilience increments, stakeholder-specific gains, stakeholder groups, and aggregated gain, thereby representing the benefit-generation process underlying resilience optimization; and (3) to support a closed decision-feedback process in which stakeholder-specific gains inform subsequent strategy prioritization. Through this structure, the framework provides a transferable basis for broader infrastructure systems, such as power, road, aviation, metro, water, and telecom systems.

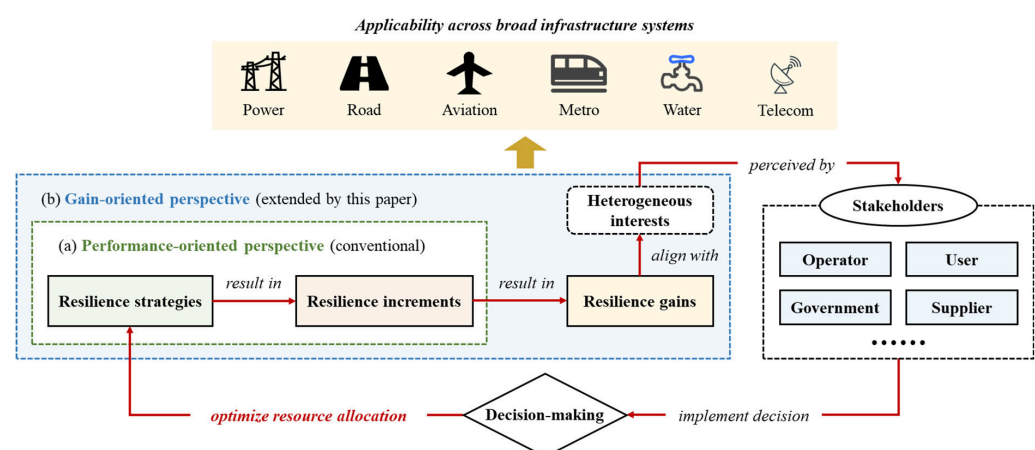


Figure 2. Infrastructure resilience optimization framework integrating stakeholder interests.

3. Methodology

To operationalize the proposed framework, a fuzzy-evidential Bayesian Network (BN) supported by fuzzy-evidential parameterization is adopted as the core modeling approach for capturing uncertain and hierarchical dependencies among resilience strategies, resilience increments, resilience gains, stakeholder groups, and aggregated gain within a transparent probabilistic structure [1,8]. BN further enables inference-based analyses, including strategy prioritization, robustness testing, and critical causal chain identification, thereby supporting the identification of key intervention pathways. Its extension into a Dynamic Bayesian Network (DBN) also allows the long-term dynamics of stakeholder-oriented resilience optimization to be captured.

The research workflow consists of three stages, as shown in Figure 3. First, BN model structuring defines the network layers, identifies nodes, and establishes causal relationships. Second, BN model development formulates the probabilistic logic and obtains conditional probability tables (CPTs) using triangular fuzzy numbers, Dempster–Shafer evidence theory, and the Leaky Noisy-Or gate model. Third, BN model analysis applies static BN analysis to prioritize strategies, test model robustness, and identify critical paths, and further uses DBN analysis to examine long-term optimization dynamics. The framework is applied to a GoA4-level urban metro system (UMS) case study in Section 4 to demonstrate its operationalization in a real infrastructure context. The case selection logic, background, and data sources are presented in Section 4.1.

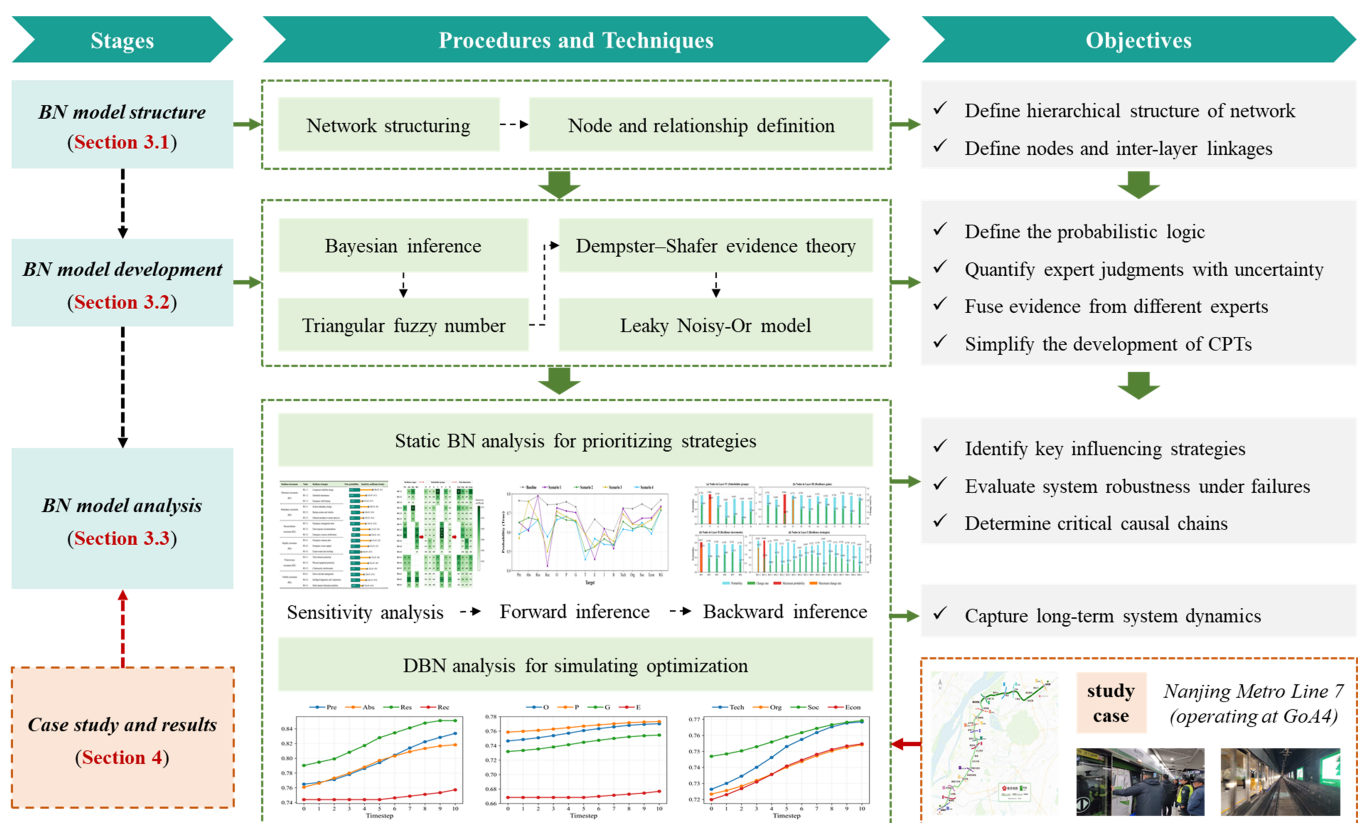


Figure 3. Research workflow.

3.1. BN Model Structure

Building upon the optimization framework in Section 2.4, a five-layer BN structure was established for modeling resilience gain generation and the subsequent aggregation process. As shown in Figure 4, the BN is organized sequentially into five layers: resilience strategies (Layer I), resilience increments (Layer II), resilience gains (Layer III), stakeholder groups

(Layer IV), and aggregated gain (Layer V). In this structure, Layers I to III characterize the generation process of resilience gains, whereas Layers III to V describe how such gains are linked to stakeholder groups and further aggregated into a system-level outcome. The nodes within each layer are accordingly defined, as detailed in Figure 4.

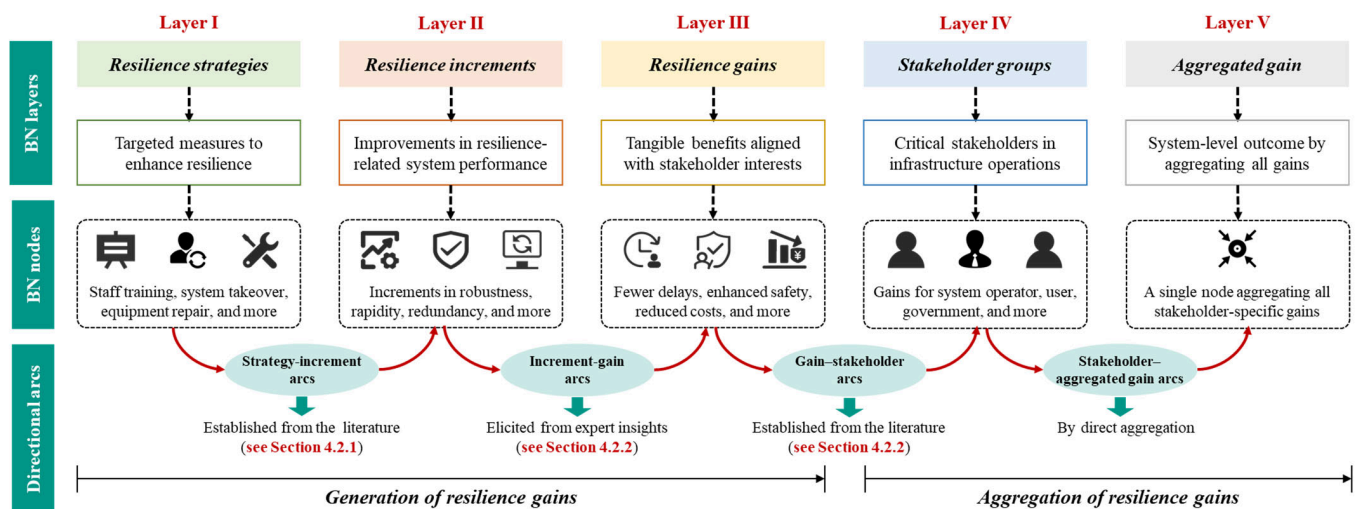


Figure 4. Definition of BN model structure and directional arcs.

After defining the BN layers and nodes, directional arcs were established only between adjacent layers in accordance with the inter-layer directional relationships illustrated in Figure 4. To reduce potential confirmation bias, these arcs were specified using a constrained inter-layer logic rather than unrestricted manual editing. Specifically,

- (1) **Strategy–increment arcs.** The Layer I–II arcs link resilience strategies to resilience increments. These arcs indicate how specific strategies contribute to resilience-property improvements and were derived from the literature and validated by experts (see Section 4.2.1).
- (2) **Increment–gain arcs.** The Layer II–III arcs link resilience increments to resilience gains. These arcs represent the process through which improvements in resilience properties lead to stakeholder-specific gain realization and were determined based on expert insights and consensus screening (see Section 4.2.2).
- (3) **Gain–stakeholder arcs.** The Layer III–IV arcs link resilience gains to stakeholder groups. These arcs indicate which stakeholder groups receive or value specific resilience gains and were established from the literature and expert validation (see Section 4.2.2).
- (4) **Stakeholder–aggregation arcs.** The Layer IV–V arcs aggregate stakeholder-group outcomes into the aggregated gain node. This aggregation reflects the contribution of stakeholder-level gains to the overall system-level resilience gain.

Accordingly, all arcs follow the forward gain-generation logic from strategies to increments, gains, stakeholders, and aggregated gain, while reverse arcs and intra-layer arcs were excluded at the structure-definition stage. The rules for defining directional causal arcs and filling the corresponding CPTs are summarized in Table 2, with detailed probabilistic parameterization provided in Sections 3.2 and 4.3.

Table 2. Rules for defining directional arcs and CPT inputs in BN.

Arc Type	Directional Logic	Evidence Basis	CPT Construction Method
Strategy–Increment	Strategies improve resilience properties	Literature + expert validation	Root priors and causal strengths processed through fuzzy-evidential parameterization
Increment–Gain	Resilience increments lead to gain realization	Expert insights + consensus screening	Fused causal strengths used as Noisy-Or inputs
Gain–Stakeholder	Gains are received or valued by stakeholders	Literature evidence + expert validation	Fused causal strengths used for CPT construction
Stakeholder–Aggregated Gain	Stakeholder gains jointly support system-level gain	Model aggregation logic	Noisy-Or aggregation based on causal-strength inputs

3.2. BN Model Development

This section explains how the BN model is probabilistically parameterized. Section 3.2.1 introduces the Bayesian inference basis, Sections 3.2.2 and 3.2.3 explain expert judgment processing and evidence fusion, and Section 3.2.4 presents CPT construction using the Leaky Noisy-Or model.

3.2.1. Bayesian Inference

Bayesian inference forms the theoretical foundation for BN model development and analysis. In a BN, variables without parent nodes (i.e., root nodes) are assigned prior probabilities, while others are defined by CPTs. Leveraging observed evidence, Bayesian inference allows the calculation of posterior probabilities [1,6,8], thus supporting the analysis of complex and uncertain practical problems. The joint probability distribution of a BN with n random variables $X_1, X_2, \dots, X_n$ is factorized as:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | \text{Parents}(X_i)) \quad (1)$$

where $\text{Parents}(X_i)$ represents a parent node of variable X_i . This formulation is based on Bayes' theorem, originally proposed by Thomas Bayes, which defines the conditional probability of an event. The classic form is:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (2)$$

where $P(A)$ is the prior probability of A; $P(B)$ is the prior probability that the event B itself is true; $P(A|B)$ is the posterior probability of A given the event B; $P(B|A)$ is the probability of the event B if hypothesis A is true.

Given the confidentiality of operational data and limited records of UMS emergency events, expert judgment is leveraged to estimate prior probabilities and CPTs [5,36]. To ensure clarity and usability in expert elicitation, all node states are defined as binary [5], where “True” denotes successful implementation of strategies or gain realization, and “False” indicates the opposite.

3.2.2. Triangular Fuzzy Number

To mitigate subjectivity in expert judgments, fuzzy set theory is applied, with assessments represented as triangular fuzzy numbers chosen for their simplicity and proven applicability in probabilistic estimation [6]. Expert judgments are elicited through a five-level linguistic scale (Very low = (0, 0, 0.3), Low = (0, 0.3, 0.5), Medium = (0.3, 0.5, 0.7), High = (0.5, 0.7, 1), Very high = (0.7, 1, 1)) and then defuzzified into probability values

using the mean area method in Equation (3), where P_{kij} denotes the probability assigned by expert k for node i in state j . This process enables the quantitative derivation of prior probabilities for root nodes and conditional probabilities for non-root nodes from expert inputs.

$$P_{kij} = \frac{a_{kij} + b_{kij} + c_{kij}}{4} \quad (3)$$

3.2.3. Dempster–Shafer Evidence Theory

Dempster–Shafer (D-S) evidence theory is employed as an intermediate step to fuse expert judgments that may diverge or conflict [6]. Unlike conventional aggregation methods, such as the arithmetic mean, it offers a structured framework for fusing multi-source information, quantifying the degree of conflict, and retaining uncertainty inherent in expert knowledge [8]. In this study, the fused D-S evidence is further transformed into probability inputs for BN parameterization, rather than being directly used as the CPT.

Let the frame of discernment be $\Theta = \{A_1, A_2, \dots, A_n\}$, where hypotheses are mutually exclusive and collectively exhaustive. A basic probability assignment (BPA) is defined as a mapping $2^\Theta \rightarrow [0, 1]$ with $m(\emptyset) = 0$ and $\sum_{A \subseteq 2^\Theta} m(A) = 1$. Subsets with $m(A) > 0$ are called focal elements. Assuming $m_1, m_2, \dots, m_p$ represent p pieces of evidence under the same frame of discernment, the Dempster rule for aggregating multiple BPAs is defined as:

$$m(A) = \begin{cases} \frac{1}{1 - \partial} \sum_{A_i \cap A_j \cap \dots \cap A_k = A} m_1(A_i) m_2(A_j) \dots m_p(A_k), & A \neq \emptyset \\ 0, & A = \emptyset \end{cases} \quad (4)$$

where the conflict coefficient $\partial \in [0, 1]$ is defined as:

$$\partial = \sum_{A_i \cap A_j \cap \dots \cap A_k = \emptyset} m_1(A_i) m_2(A_j) \dots m_p(A_k) < 1 \quad (5)$$

A larger ∂ value indicates stronger conflict among expert evidence. In this study, expert assessments, initially expressed as triangular fuzzy numbers, are converted into interval probabilities and subsequently mapped into BPAs. For each node x_i , a BPA matrix $M(x_i)$ is constructed as:

$$M(x_i) = \begin{pmatrix} m_1(x_i) \\ m_2(x_i) \\ \dots \\ m_k(x_i) \end{pmatrix} = \begin{pmatrix} m_1(x_{i0}) & m_1(x_{i1}) & \dots & m_1(x_{i(t_i-1)}) \\ m_2(x_{i0}) & m_2(x_{i1}) & \dots & m_2(x_{i(t_i-1)}) \\ \dots & \dots & \dots & \dots \\ m_k(x_{i0}) & m_k(x_{i1}) & \dots & m_k(x_{i(t_i-1)}) \end{pmatrix} \quad (6)$$

where $m_k(x_{ij})$ represents the BPA assigned by expert k for the state j of node x_i and the constraint $\sum_{j=0}^{t_i-1} m_k(x_{ij}) = 1$ holds (t_i represents the total number of states of x_i). Using Dempster's rule in Equations (4) and (5), the multi-expert BPAs are iteratively fused with conflict coefficients computed at each step, and the fused results are normalized to yield the probability distribution for each node, as summarized in Algorithm 1. The resulting values provide the prior probabilities for root nodes and the causal-strength inputs used to construct CPTs of non-root nodes through the Noisy-Or model.

Algorithm 1. Dempster–Shafer evidence theory (fusion for node x_i)

Input: BPA matrix $M(x_i)$, where the k -th row is the BPA vector assigned by expert k :

$$m_k(x_i) = [m_k(x_{i0}), m_k(x_{i1}), \dots, m_k(x_{i(t_i-1)})]$$

Output: Fused probability distributions $P(x_i)$ of node x_i over all states

Steps:

```

1: # Step 1: Initial fusion of expert 1 and 2
2:   $R_1 = \text{outer\_product}[m_1(x_i)^T, m_2(x_i)]$ 
3:   $\partial_1 = \text{SUM}(R_1) - \text{SUM}(\text{diag}(R_1))$ 
4:  # Step 2: Iteratively fuse the remaining experts
5:  for  $k = 3$  to  $k$  do:
6:     $d_{k-1} = \text{diag}(R_{k-2})$ 
7:     $R_{k-1} = \text{outer\_product}[d_{k-1}, m_k(x_i)]$ 
8:     $\partial_{k-1} = \text{SUM}(R_{k-1}) - \text{SUM}(\text{diag}(R_{k-1}))$ 
9:  end for
10: # Step 3: Compute the total conflict coefficient
11:  $\partial_{\text{total}} = \sum_{r=1}^{k-1} \partial_r$ 
12: # Step 4: Compute the fused probability distribution
13: If  $\partial_{\text{total}} < 1$  then:
14:    $d^{\text{final}} = \text{diag}(R_{k-1})$ 
15:   for  $j = 0$  to  $t_{i-1}$  do:
16:      $P(x_{ij}) = d_j^{\text{final}} / (1 - \partial_{\text{total}})$ 
17:   end for
18: else
19:   for  $j = 0$  to  $t_{i-1}$  do:
20:      $P(x_{ij}) = 0$ 
21:   end for
22: end if
23: return  $P(x_i)$ 

```

It should be clarified that D-S evidence theory is not directly embedded into the BN CPTs as raw belief masses. Rather, it serves as an intermediate fusion mechanism for deriving BN-compatible probabilistic inputs. To avoid non-normalization or Zadeh-type normalization paradoxes under highly conflicting expert evidence, the fused masses obtained from Algorithm 1 are accepted only when the conflict coefficient ∂ satisfies the mathematical validity condition $\partial < 1$, so that the normalization denominator $1 - \partial$ remains positive. Since Dempster's rule normalizes the non-conflicting mass by $1 - \partial$, the accepted outputs form a valid probability distribution satisfying $P(\text{True}) + P(\text{False}) = 1$. These normalized probabilities are then used as either root-node priors or as causal-strength inputs for Leaky Noisy-Or CPT construction. If ∂ approaches one, indicating near-total conflict among expert evidence, the corresponding judgments are returned for expert rechecking, discussion, or discounting before parameterization. Algorithm 2 summarizes this interface between fuzzy expert judgments, evidence fusion, and BN probability inputs.

Algorithm 2. Fuzzy-evidential parameterization interface for BN probability inputs**Input:** Expert linguistic judgment matrix $L(x_i)$ for node x_i or link $x_j \rightarrow x_i$ **Output:** Root-node prior probability $P(x_i)$ or causal strength θ_{ji} **Steps:****1: # Step 1: Transform linguistic judgments into BPA vectors****2: for** $k = 1$ **to** m **do:****3:** Convert $l_k(x_i)$ into $TFN_k(x_i)$ and defuzzify it as $p_k(x_i)$ **4:** Construct the BPA vector $m_k(x_i)$ assigned by expert k **5: end for****6: # Step 2: Apply Dempster–Shafer evidence fusion****7:** Construct BPA matrix $M(x_i)$ from all $m_k(x_i)$ **8:** Apply Algorithm 1 to obtain $P(x_i)$ and ∂_{total} **9: # Step 3: Check evidence conflict****10: If** ∂_{total} **approaches** 1 **then:****11:** Return $L(x_i)$ for expert rechecking or discounting**12: end if****13: # Step 4: Generate BN probability inputs****14: If** x_i **is a root node** **then:****15:** Use $P(x_i)$ as the prior probability distribution of x_i **16: else****17:** Set $\theta_{ji} = P(x_{i1})$ for Noisy-Or CPT construction**18: end if****19: return** $P(x_i)$ or θ_{ji}

3.2.4. Leaky Noisy-Or Model

Following fuzzy-evidential fusion, the normalized probability inputs are used to parameterize the BN. For root nodes, the fused $P(True)$ and $P(False)$ values directly define prior probabilities. For non-root nodes, the fused probabilities associated with retained parent–child arcs are treated as causal-strength inputs and expanded into CPTs using the Leaky Noisy-Or model [5,8]. This model reduces the computational burden of CPT development by assuming that each parent node x_i independently contributes to the activation of the child node Y . When only one parent node x_i is “True” and all other parent nodes are “False”, the probability that Y is “True” is defined as:

$$R_i = P(Y = True \mid x_i = True, x_j = False, \forall i \neq j) \quad (7)$$

To account for the potential influence of unidentified causes, the Leaky Noisy-Or model introduces a leaky node x_L , which represents the cumulative effect of all unknown factors. Following prior infrastructure resilience studies [6], the leak probability R_L is conservatively set to 0.01, corresponding to a 99% confidence level under Gaussian distribution. For each CPT row, the complementary probability is defined as: $P(Y = False \mid X) = 1 - P(Y = True \mid X)$, thereby ensuring row-wise normalization of the CPT.

The Leaky Noisy-Or formulation should not be interpreted as a deterministic or linear utility-conversion equation. Rather, it represents a probabilistic activation mechanism under monotonic and conditionally independent parent-effect assumptions. While suitable for expert-elicited BN modeling when full CPT specification is infeasible, this formulation limits the representation of threshold effects, saturation effects, and synergistic interactions among parent nodes.

3.3. BN Model Analysis

The BN model analysis consists of two components: Section 3.3.1 presents static BN analysis for strategy prioritization, robustness validation, and critical causal chain identification, while Section 3.3.2 introduces DBN analysis for simulating long-term optimization dynamics under resource constraints.

3.3.1. Static BN Analysis for Strategy Prioritization

(1) Sensitivity analysis. The first step, sensitivity analysis, identifies key influencing strategies by evaluating their relative importance in the network. In this study, it quantifies how minor variations in the prior probabilities of root nodes, corresponding to variations in resources allocated to strategy implementation, affect the posterior probability of the target node [5]. This allows the prioritization of nodes according to their influence on predictive outcomes. The sensitivity coefficient is calculated using the following formula:

$$\gamma(x_i, y_i) = \frac{\varphi(y_i) - \theta(y_i)}{\varphi(x_i) - \theta(x_i)} \quad (8)$$

where $\gamma(x_i, y_i)$ is the sensitivity coefficient between input node x_i and target node y_i , $\theta(x_i)$ and $\theta(y_i)$ denote their prior probabilities, and $\varphi(x_i)/\varphi(y_i)$ denote the corresponding posterior probabilities after the update.

(2) Forward inference. The second step estimates the probability distribution of the target nodes based on known evidence from upstream nodes [6], by propagating information forward through the defined causal relationships and CPTs. In this study, it is used to evaluate system responses under predefined evidence and to validate model robustness, particularly for scenarios involving failures of key influential strategies. The general form of forward inference is given by:

$$P(\text{Target} = t) = \sum_{x_1, x_2, \dots, x_n} P(\text{Target} = t | x_1, x_2, \dots, x_n) \cdot P(x_1, x_2, \dots, x_n) \quad (9)$$

where $P(\text{Target} = t | x_1, x_2, \dots, x_n)$ denotes the conditional probability of the target node being in state t given a specific joint state combination of the upstream nodes, and $P(x_1, x_2, \dots, x_n)$ denotes the probability of that joint state combination.

(3) Backward inference. The third step identifies critical causal chains underlying system-level outcomes. Starting with evidence at a target node, information is propagated backward through the BN to infer posterior probabilities of upstream nodes [6]. In this study, this analysis is performed by setting Aggregated Gain (Layer V) to an evidence state of full success ($P(\text{True}) = 100\%$), thus identifying key strategies and associated paths that most strongly support system-level outcomes. The process for inferring posterior probabilities under given evidence is as follows:

$$P(x_i | \text{Target} = t) = P(\text{Target} = t | x_i) \cdot P(x_i) / P(\text{Target} = t) \quad (10)$$

3.3.2. DBN Analysis for Simulating Optimization

To complement the static analysis, a DBN analysis is performed to capture the long-term dynamics of resilience optimization [1]. By accounting for temporal causality, the DBN offers a robust framework to model sequential decisions and system state transitions over time. The DBN operates under the first-order Markov assumption [5], where (1) the network structure and CPTs remain fixed; and (2) the state at timestep $t + 1$ depends solely on the state at timestep t . As illustrated in Figure 5, the DBN unfolds across discrete timesteps $(0, 1, \dots, n)$, with nodes replicated in each slice. Intra-slice arcs (solid lines) represent

dependencies within a single timestep, while inter-slice arcs (dashed lines) capture temporal dependencies between adjacent slices.

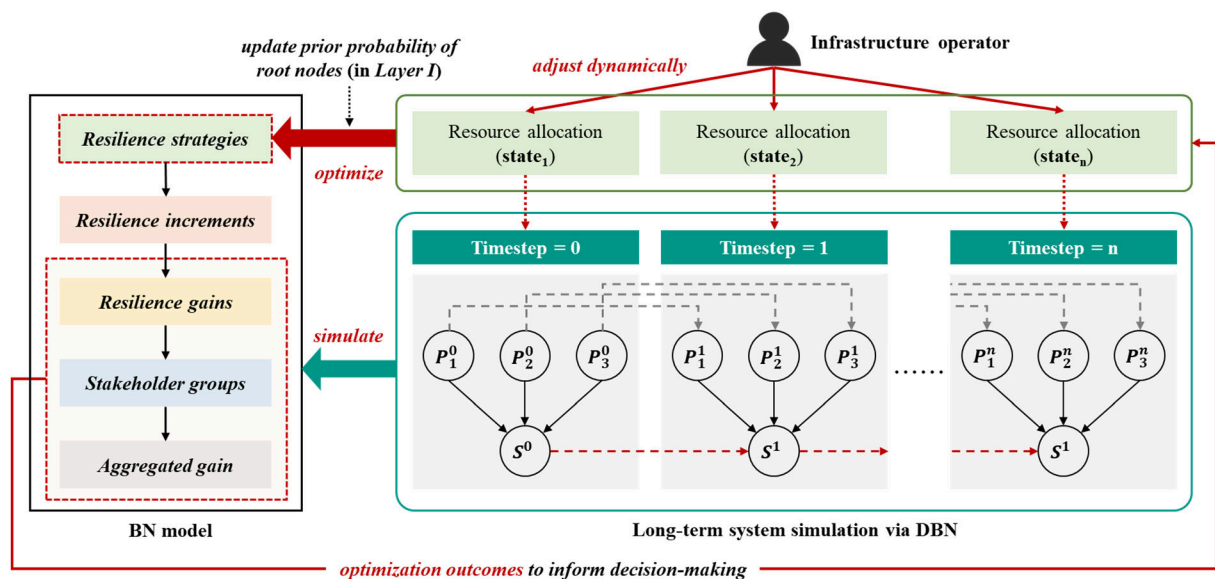


Figure 5. DBN process for simulating infrastructure operator-centered optimization.

In this study, the DBN simulates the operator-centered optimization process as a dynamic decision-feedback loop. As illustrated in Figure 5, the infrastructure operator acts both as a resource allocator and as a stakeholder that benefits from improved resilience. At each timestep, resource allocation is determined by three practical considerations: (1) the prioritization of key strategies based on the operator's preferred resilience gains, (2) resource constraints that limit how many strategies can be reinforced per step, and (3) a reward-penalty mechanism that adjusts future decisions according to previous optimization outcomes. These conditions are modeled through updates to the prior probabilities of the root nodes (i.e., resilience strategies). The updated strategies then propagate through the DBN to affect resilience increments, resilience gains, stakeholder groups, and the aggregated gain over time.

4. Case Study and Results

This section applies the proposed framework to a UMS case and reports the analytical results. Section 4.1 introduces the case background and data collection, Sections 4.2 and 4.3 develop the BN structure and baseline model, and Sections 4.4 and 4.5 present the static and dynamic BN analysis results.

4.1. Case Selection and Data Collection

This study selects Nanjing Metro Line 7, the only UMS line in Nanjing operating at GoA4, as an information-oriented single case for operationalizing the proposed framework. Following Flyvbjerg's logic [37], the case was selected to maximize information utility rather than statistical representativeness. Line 7 is suitable because it combines high automation, complex subsystem coupling, multi-stakeholder involvement, and lifeline mobility functions, making it an appropriate empirical context for examining how resilience strategies are linked to stakeholder-specific gains. As shown in Figure 6a, Nanjing Metro Line 7 comprises 27 stations, including 13 transfer stations, spans 35.49 km entirely underground, and carries an average daily ridership exceeding 260,000 passengers. The line has also accumulated operational and emergency management experience from disruption events, including platform screen door ruptures and malfunctions, power short circuits,

and other operational incidents, as illustrated in Figure 6b,c. Access to field investigations and expert consultation further supports its suitability as the empirical case.

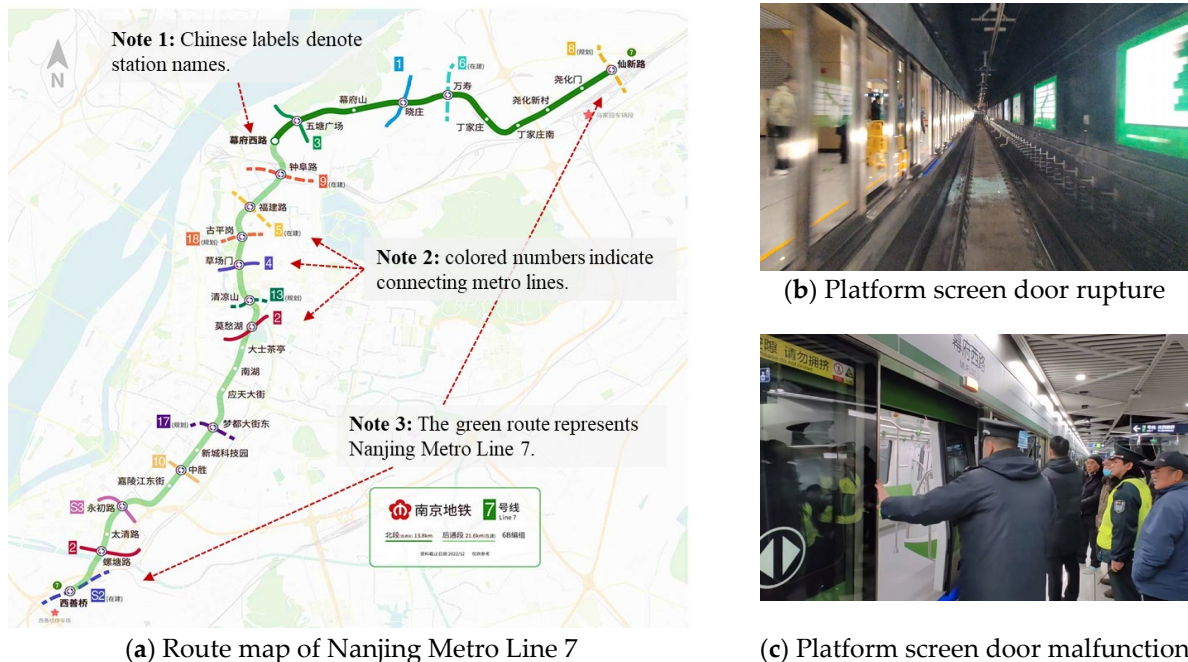


Figure 6. Selected case study: Nanjing Metro Line 7 (operating at GoA4).

Due to the sensitive nature of metro operational data and associated public safety concerns, objective modeling data are often restricted. Therefore, expert judgment was used as the primary data source [5]. Two types of data were collected. First, BN model-structure information, including resilience strategies, resilience increments, resilience gains, stakeholder groups, and inter-layer arcs, was derived from literature review and expert validation. Second, probabilistic parameter data, including root-node priors and inter-layer dependency strengths, were elicited through structured expert questionnaires and processed through the fuzzy-evidential BN parameterization procedure.

The expert panel was assembled to balance practical and theoretical insights. It included practitioners from government agencies and Nanjing Metro with expertise in UMS operations and emergency management, as well as academic scholars specializing in infrastructure resilience. Consistent with established multi-criteria decision-making studies [6,8], eight experts were invited, with demographic information provided in Table A1 (Appendix A). Although the panel could not fully cover all stakeholder groups involved in UMS operations, its professional experience and domain knowledge support the assessment of resilience strategies, stakeholder interests, and inter-layer dependencies.

The expert consultation followed a sequential protocol to support BN topology validation and probability parameterization. First, the panel validated the selected resilience strategies, resilience properties, gains, stakeholder groups, and candidate inter-layer arcs, thereby refining the BN nodes and directional arcs. Subsequently, through structured questionnaires refined from prior research [5] (see Tables A2 and A3 in Appendix A), the experts: (1) assessed the likelihood of successful implementation for each strategy to set the priors of Layer I nodes; (2) mapped resilience increments to gains using a majority consensus threshold of at least 50% to screen the linkages from Layer II to III; and (3) quantified the retained inter-layer dependencies for subsequent CPT construction.

4.2. BN Structure Development

Following the directional arc rules defined in Section 3.1, the case-specific BN structure was developed by identifying, validating, and screening directional arcs across the five model layers. Strategy–increment and gain–stakeholder arcs were derived from literature evidence and expert validation (Sections 4.2.1 and 4.2.2), while increment–gain arcs were screened through expert consultation based on the consensus rule described in Section 4.1.

4.2.1. From Resilience Strategies to Increments (Layers I and II)

UMS operating at GoA4 is characterized by high functional complexity, functioning as tightly coupled socio-technical systems with interdependent components and intensive human–machine interaction. Consequently, resilience modeling must encompass both technical reliability and socio-organizational dynamics under emergency scenarios. Drawing on established theory [6], this study augments the traditional 4Rs framework (Robustness, Redundancy, Resourcefulness, and Rapidity) by incorporating two additional properties: Protectiveness and Visibility.

A key contribution of this stage is the preliminary definition of BN nodes for Layers I and II. These six properties constitute the BN nodes at Layer II, representing multidimensional resilience increments. By systematically identifying resilience strategies from the literature and expert surveys (Table 3) and aligning them with these properties, the fundamental nodes for Layer I were established. Crucially, this alignment process also determined the directional arcs from Layer I to Layer II, thereby capturing the causal dependencies between strategy implementation and the resulting resilience increments. Furthermore, the implicit mapping between these properties and the four resilience stages, covering Preparation (Pre), Absorption (Abs), Response (Res), and Recovery (Rec), is explicitly integrated into the model structure.

Table 3. Identified resilience strategies across six key properties.

Resilience Increments	Resilience Stages	Code	Resilience Strategy (with Brief Description)	Source
Robustness increments (RI 1)	Abs & Res	RS 1-1	Component reliability design. Integration of high-reliability modules (braking, traction, signaling, SPKS) to reduce faults and limit risk propagation.	[31]
		RS 1-2	Scheduled maintenance: Preventive, lifecycle-based interventions for critical subsystems to mitigate latent failures and extend service life.	[38]
		RS 1-3	Emergency staff training: Structured training for dispatchers, station staff, and maintenance teams to strengthen emergency response capability.	[32]
Redundancy increments (RI 2)	Pre & Res	RS 2-1	System redundancy design: Redundant configurations for interlocking logic and train control to ensure fault tolerance and seamless failover.	[34]
		RS 2-2	Backup systems and vehicles: Standby systems and reserve rolling stock allocated during disruptions to restore service continuity.	[39]
		RS 2-3	Onboard attendant or remote takeover: Human intervention as backup safety mechanism when automation fails.	[40]

Table 3. Cont.

Resilience Increments	Resilience Stages	Code	Resilience Strategy (with Brief Description)	Source
Resourcefulness increments (RI 3)	Pre & Rec	RS 3-1	Emergency management team: Multidisciplinary operator team (operations, maintenance, cybersecurity) for coordinated system-wide responses.	Expert survey
		RS 3-2	Fault-response recommendation: Decision-support systems with data fusion and anomaly detection for real-time fault identification and guided responses.	[41]
		RS 3-3	Emergency resource mobilization: Rapid deployment of crews, spare parts, and specialists supported by resource-allocation models.	[42]
Rapidity increments (RI 4)	Rec	RS 4-1	Emergency response plan: Predefined procedures assigning roles, workflows, and collaboration protocols for timely recovery actions.	[43]
		RS 4-2	Emergency rescue support: Cooperation with external fire/first-aid services for timely containment in severe disturbances.	[21]
		RS 4-3	System restart and switching: Fast switchover mechanisms (backup control units, links, processors) to minimize downtime.	[34]
Protectiveness increments (RI 5)	Pre & Abs	RS 5-1	Track intrusion protection: Boundary fencing, alarms, and sensor-based detection integrated with braking systems.	[44]
		RS 5-2	Physical equipment protection: Enclosures, vibration isolation, and shielding to safeguard critical hardware.	Expert survey
		RS 5-3	Cybersecurity reinforcement: Multi-layered defense (firewalls, intrusion detection, monitoring) to protect CBTC and cyber-physical systems.	[33]
Visibility increments (RI 6)	Abs & Rec	RS 6-1	End-to-end data management: Real-time acquisition, synchronization, and monitoring of operational data for anomaly detection and performance tracking.	[26]
		RS 6-2	Intelligent fault diagnostics: Expert systems to identify degradation signals, assess disturbance severity, and generate fault interpretations.	[35]
		RS 6-3	Multi-channel information platform: PIS, apps, and webs for transparent communication of service updates, safety alerts, and evacuation guidance.	[29]

4.2.2. From Resilience Gains to Stakeholders (Layers III and IV)

By integrating the operational characteristics of GoA4-level UMS with expert insights, seven critical stakeholder groups were identified: Operator (O), Passenger (P), Government (G), Technology supplier (T), Emergency agency (E), Insurance provider (I), and Trackside business (B). These groups constitute the BN nodes at Layer IV. Correspondingly, specific resilience gains reflecting the strategic interests of these stakeholders were derived from academic literature and expert surveys (Table 4). This process also establishes the nodes at Layer III and defines the directional arcs from Layer III to Layer IV, which represent the relevance of specific resilience gains to different stakeholder groups.

Table 4. Identified resilience gains across seven critical stakeholders.

Stakeholder Groups	Code	Resilience Gain (with Brief Description)	Dimension	Source
Operator (O)	O1	Fewer operational interruptions: Service continuity maintained under disturbances	Tech & Org	[12]
	O2	Reduced handling costs: Lower repair expenses and liability claims	Org & Econ	[45]
	O3	Improved reputation: Enhanced public trust and long-term revenue	Soc	[30]
Passenger (P)	P1	Enhanced passenger safety: Reduced risks during system failures or hazards	Soc	[5]
	P2	Reduced passenger delays: Minimized disturbances to schedules and commuting time	Soc & Econ	[12]
	P3	Improved passenger comfort: Reliable and acceptable travel experience under abnormal conditions	Soc	[29]
Government (G)	G1	Enhanced public safety: Minimized risk exposure and incident severity	Soc	[5]
	G2	Improved infrastructure service: Reliable operation supporting urban sustainability	Tech & Org	[46]
Technology supplier (T)	T1	Fewer equipment-related claims: Reduced technical malfunctions and warranty liabilities	Tech & Econ	Expert survey
Emergency agency (E)	E1	Improved emergency response: Faster, coordinated interventions under critical events	Org	[21]
Insurance provider (I)	I1	Reduced insurance payouts: Fewer and less severe insurable incidents	Econ	Expert survey
Trackside business (B)	B1	Stabilized commercial revenue: Consistent passenger flow sustaining business income	Econ	[47]

Subsequently, the directional arcs between Layer II and Layer III were screened based on an expert consultation protocol requiring a consensus threshold of at least 50% agreement (see Table A4 in Appendix B). This systematic screening procedure improves the traceability of the BN topology and ensures that the retained arcs reflect the transition from performance-level resilience increments to stakeholder-specific gains. Furthermore, Table 4 incorporates the implicit mappings between these resilience gains and their underlying dimensions of Technical (Tech), Organizational (Org), Social (Soc), and Economic (Econ) for further analysis.

4.3. Results of Baseline BN Model Development

Following structure development, the BN model was parameterized according to the procedures described in Section 3.2. For Layer I root nodes, expert judgments on strategy implementation success were converted into prior probabilities through triangular fuzzy numbers and D-S evidence fusion. For non-root nodes, experts evaluated the causal strength of each retained parent–child arc, defined as the probability that the child node is activated when the corresponding parent node is active and other parent nodes are inactive. These fused causal-strength inputs were then expanded into complete CPTs using the Leaky Noisy-Or model. For each CPT row, the complementary probability was defined as $P(Y = \text{False}|X) = 1 - P(Y = \text{True}|X)$, ensuring row-wise normalization. Due to space constraints, the key conditional dependencies from Layer II to Layer III are presented in Table A5 (Appendix B).

The BN model was constructed using the GeNIe graphical interface (academic version 5.0), incorporating the predefined network structure, node hierarchy, and derived probabilistic parameters. A baseline BN model was subsequently generated through probabilistic inference in the absence of external evidence. The resulting hierarchical model (see Figure 7) displays the marginal probability distributions of all nodes under normal conditions, serving as a benchmark for scenario analysis and resilience evaluation. Following model development, static BN analysis (sensitivity analysis, as well as forward and backward inference) and DBN analysis were performed using SMILE (academic version 2.4.0), the underlying inference engine of GeNIe, with execution integrated via Python (version 3.9.12).

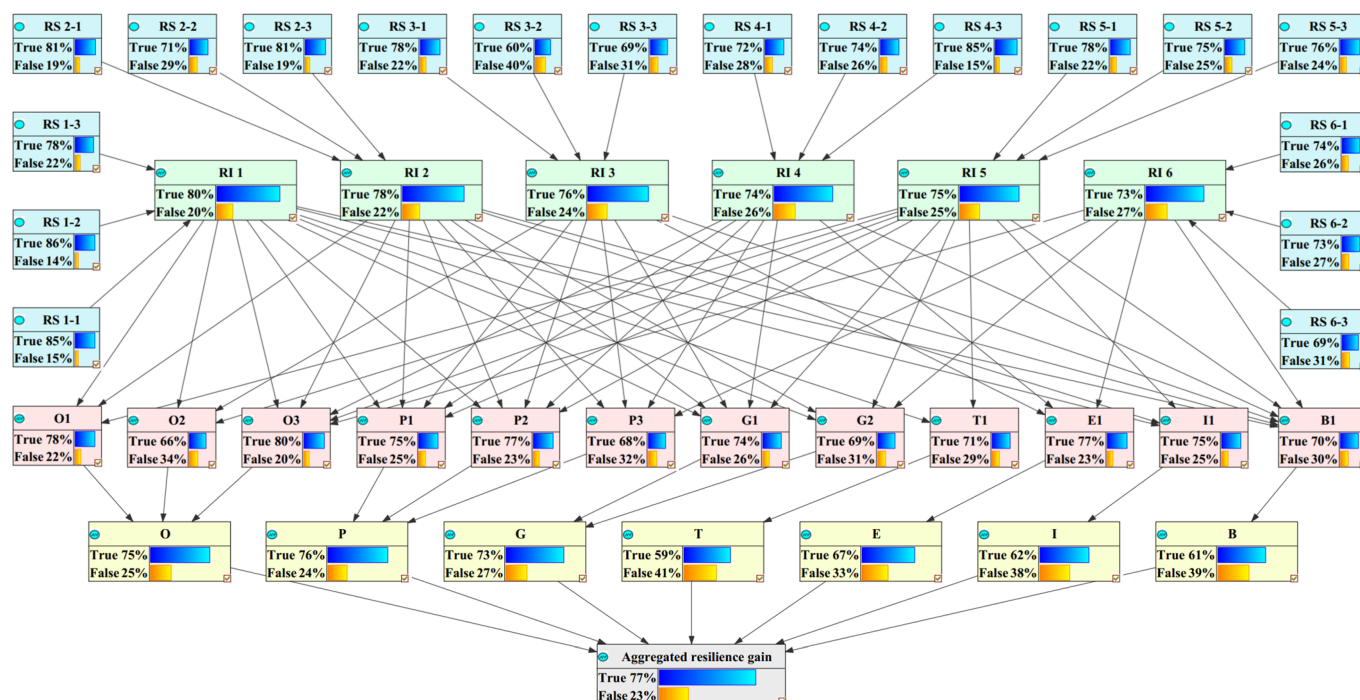


Figure 7. Baseline BN model.

4.4. Results of Prioritizing Strategies Through Static BN Analysis

This section reports the static BN results for strategy prioritization and causal interpretation. Section 4.4.1 presents sensitivity-based ranking, Section 4.4.2 validates model robustness through forward inference, Section 4.4.3 identifies critical causal chains through backward inference, and Sections 4.4.4 and 4.4.5 further examine parameter robustness and compare FEBN with non-evidence BN baselines.

4.4.1. Strategy Ranking Determined by Sensitivity Analysis

Sensitivity analysis was first performed to identify influential strategies for aggregated resilience gain at Layer V. Figure 8 presents the sensitivity coefficients, ranks, and prior probabilities of all root nodes. The top five strategies are component reliability design (2.90×10^{-3} , rank 1), emergency response plan (2.47×10^{-3} , rank 2), emergency resource mobilization (2.38×10^{-3} , rank 3), track intrusion protection (2.33×10^{-3} , rank 4), and fault-response recommendation (2.31×10^{-3} , rank 5). These strategies represent high-leverage intervention domains for improving system-level resilience gain under practical resource constraints.

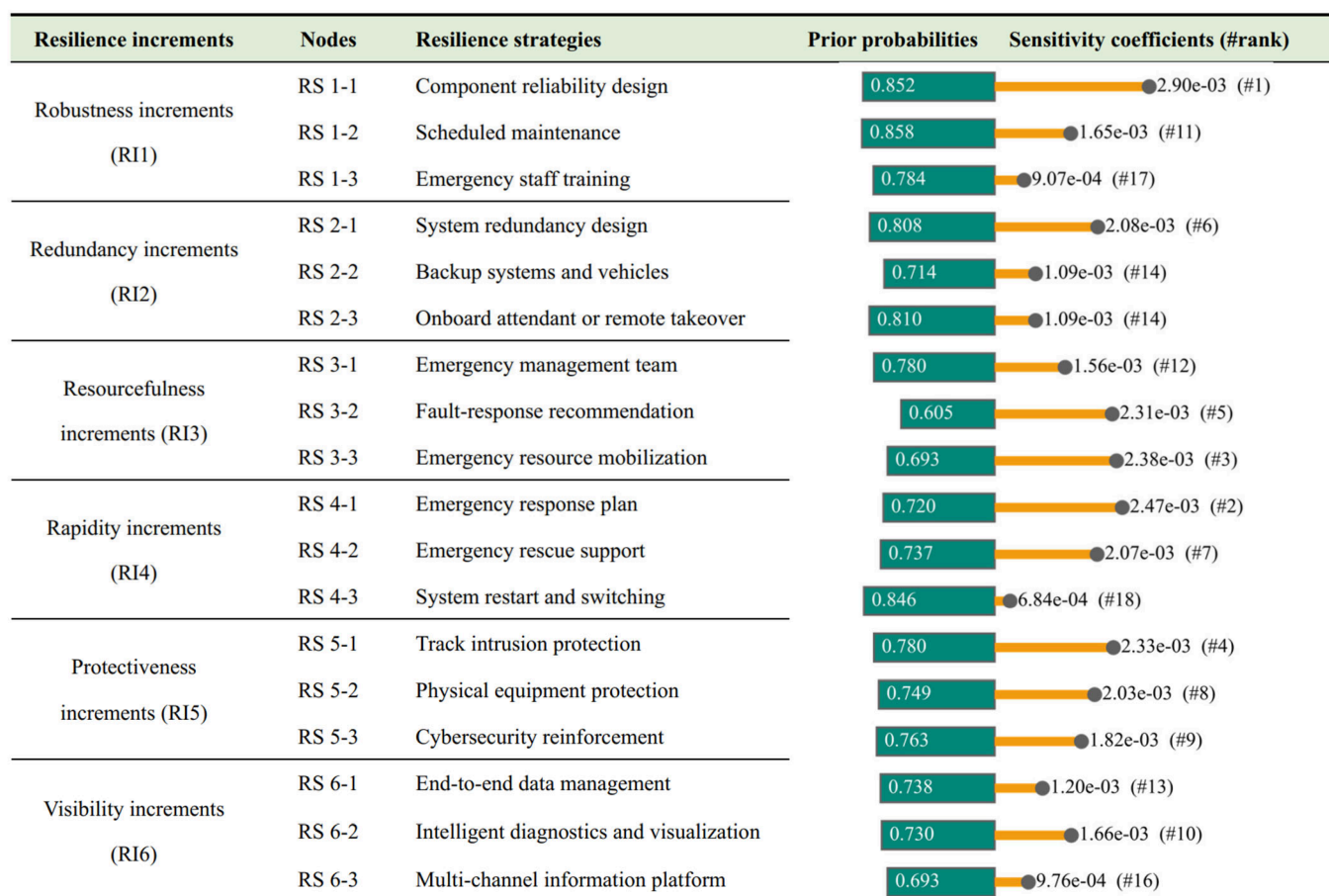


Figure 8. Sensitivity coefficients of root nodes (resilience strategies) to the aggregated gain.

The ranking results indicate that proactive and preparedness-oriented interventions play a particularly important role. Strategies such as component reliability design and emergency response planning help anticipate, absorb, and control disruption impacts before they escalate, thereby contributing to operational stability and service continuity. This finding is consistent with established resilience research emphasizing proactive resilience enhancement [5].

To further reveal heterogeneous strategy effects, sensitivity analysis was extended across resilience stages (Pre, Abs, Res, and Rec), stakeholder groups (O, P, G, T, E, I, and B), and gain dimensions (Tech, Org, Soc, and Econ). Since resilience stages and gain dimensions are not explicitly represented as BN nodes, their probabilities were approximated by averaging the corresponding resilience increment and gain nodes defined in Section 4.2, whereas stakeholder group nodes were directly used. Figure 9 visualizes the ranking patterns across these dimensions.

The results show that different strategies contribute to different resilience stages, stakeholder groups, and gain dimensions. For example, component reliability design (RS 1-1) is more influential for operator-related, technical, and economic gains, whereas emergency resource mobilization (RS 3-3) is more prominent in preparation, recovery, and emergency-related dimensions. Some strategies also show no sensitivity in specific dimensions due to absent BN linkages; for instance, RS 1-1 has no sensitivity in the preparation stage, reflecting its stronger association with absorbing and controlling disruption impacts rather than pre-disruption preparation. Overall, these findings indicate that resilience gain is a multidimensional and stakeholder-dependent outcome shaped by distinct strategy pathways.



Figure 9. Ranks of sensitivity coefficients across resilience stages, stakeholder groups, and gain dimensions.

4.4.2. Model Robustness Validated by Forward Inference

Forward inference was conducted to evaluate model robustness when key influential strategies fail. Four scenarios were constructed based on the top-ranked strategies in different analytical dimensions (Figure 9), namely recovery-focused (scenario 1), passenger-focused (scenario 2), organizational-focused (scenario 3), and aggregated outcome-focused (scenario 4). In each scenario, the corresponding five root nodes were set to the failure state, while other nodes were left unfixed. The posterior probabilities of the target nodes were then compared with the baseline state, as shown in Figure 10.

After imposing the failure states of the corresponding key strategies, the posterior probabilities of the target nodes declined across all four scenarios. The recovery node (Rec) dropped most sharply, from 74% to 42%, while the passenger-related node (P), organizational gain node (Org), and aggregated resilience gain node (RG) decreased from 74% to 50%, 63%, and 68%, respectively. These results confirm that the strategies identified by sensitivity analysis have substantial influence on the generation of corresponding resilience gains.

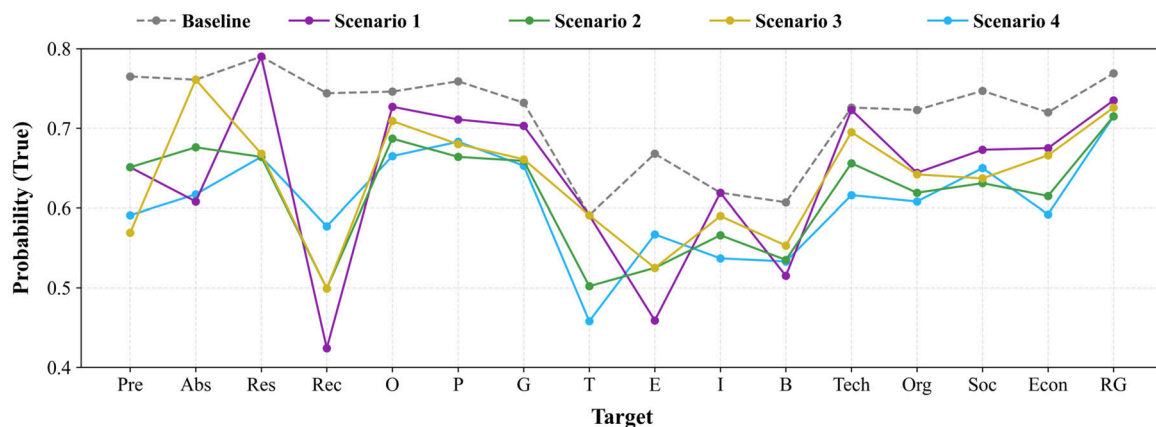


Figure 10. Comparison of posterior probabilities under different scenarios.

Nevertheless, the decline in RG remained relatively limited, within approximately 6% across scenarios. This suggests that system-level resilience gain is not dependent on a single strategy, but is jointly sustained by multiple strategic pathways and cross-stakeholder contributions. The larger declines in resilience stage nodes (Pre, Abs, Res, and Rec) further indicate an attenuation effect in the hierarchical BN structure, where strategy failures first affect resilience capabilities and are then partially absorbed through downstream gain aggregation.

4.4.3. Critical Causal Chains Identified by Backward Inference

To perform backward inference, the system-level outcome RG (Layer V) was assigned an evidence state of complete success (i.e., $P(RG = \text{True}) = 100\%$). The maximum-posterior-probability path identified in Figure 11 is: Scheduled Maintenance (RS 1-2, Layer I) → Robustness increments (RI 1, Layer II) → Reduced Passenger Delays (P2, Layer III) → Gains for Passenger (P, Layer IV) → Resilience Gain (RG, Layer V). This path shows that scheduled maintenance contributes to system-level resilience gain by strengthening robustness and reducing passenger delays. It also indicates that resilience strategies should not be viewed merely as technical safeguards, but as interventions that generate tangible stakeholder-valued benefits.

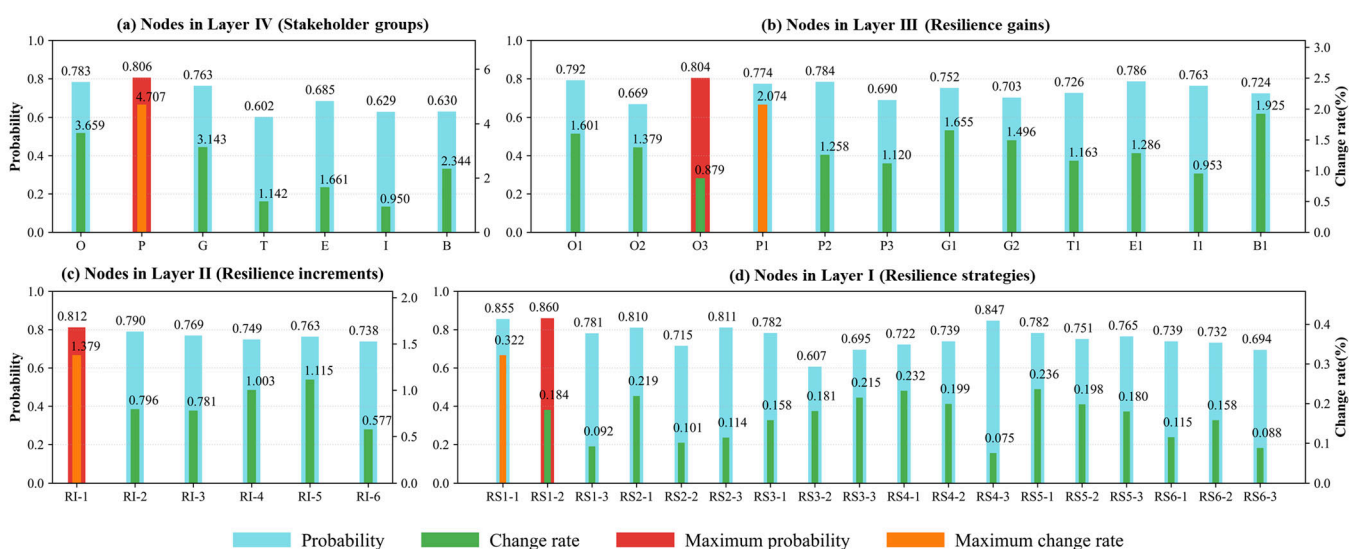


Figure 11. Comparison of critical node selection during backward inference.

A complementary change-rate analysis was further conducted to identify nodes most responsive to the target evidence. As shown in Figure 11, the posterior-probability and change-rate criteria yield partially different causal paths, with discrepancies mainly observed in Layer I and Layer III. Both paths highlight passengers as a key stakeholder and remain anchored in robustness improvement, but they emphasize different gain nodes, namely reduced passenger delays/enhanced passenger safety and improved reputation. At the strategy level, the change-rate path gives greater prominence to component reliability design (RS 1-1), which is also the top-ranked root node in the sensitivity analysis, whereas the maximum-posterior-probability path emphasizes scheduled maintenance (RS 1-2), which ranks 11th in sensitivity.

This divergence suggests that backward inference and sensitivity analysis capture different aspects of causal importance: the former identifies high-probability gain-generation paths, while the latter emphasizes strategies with stronger marginal influence on system-level outcomes. These findings motivate the DBN analysis in Section 4.5, which further examines how resilience gain evolves under long-term optimization.

4.4.4. Global Sensitivity and Robustness Under Parameter Perturbations

To further examine whether the FEBN results are robust to joint parameter uncertainty, a global parameter perturbation analysis was conducted. The prior probabilities of root nodes and the Noisy-Or causal-strength parameters were randomly perturbed within three relative uncertainty ranges: $\pm 5\%$, $\pm 10\%$, and $\pm 20\%$, representing mild, moderate, and strong uncertainty, respectively. For each uncertainty level, 1000 Monte Carlo runs were performed, and all perturbed probabilities were constrained within the valid probability interval. The posterior probability of Aggregated Gain and the stability of strategy rankings were recalculated for each run.

Figure 12a shows that the distribution of $P(RG = \text{True})$ remains centered around the baseline FEBN result under all perturbation levels. The mean probabilities are 0.769, 0.770, and 0.768 under mild, moderate, and strong perturbations, respectively. Although stronger uncertainty widens the posterior-probability intervals, the central tendency of Aggregated Gain remains stable. Specifically, the 95% interval widens from [0.749, 0.788] under $\pm 5\%$ perturbation to [0.715, 0.813] under $\pm 20\%$ perturbation. This suggests that parameter uncertainty mainly increases output dispersion rather than changing the main system-level conclusion.

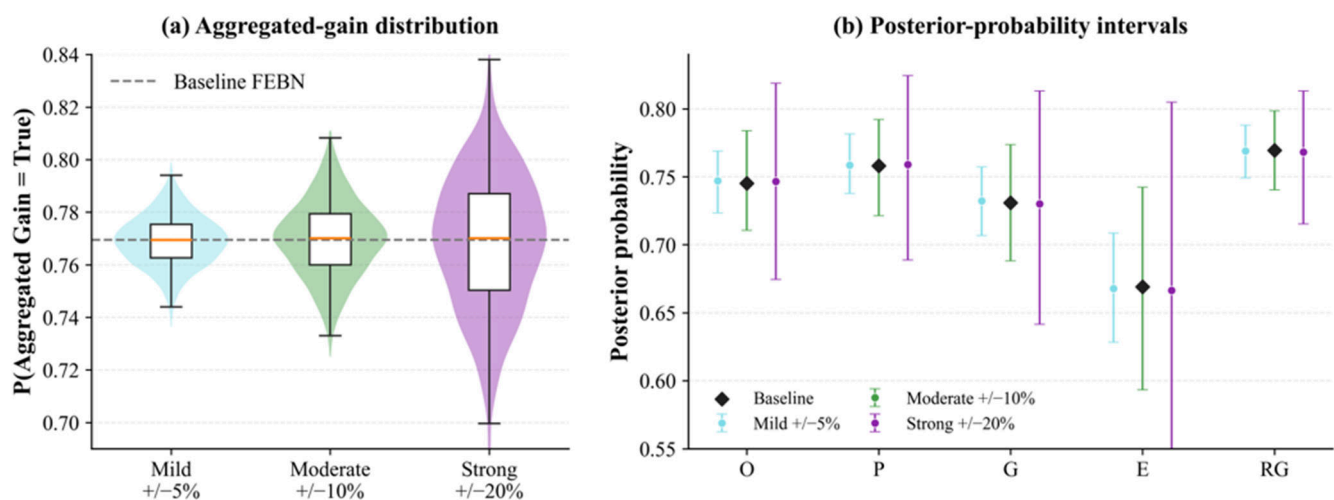


Figure 12. Global robustness profile under joint parameter perturbations.

Table 5 further summarizes the robustness and ranking-stability statistics under the three perturbation levels. The ranking results provide a more nuanced robustness interpretation. The strategy-ranking Spearman correlations are 0.792, 0.730, and 0.569 under mild, moderate, and strong perturbations, respectively, while the Top-5 overlap ratios are 0.637, 0.612, and 0.514. Therefore, the high-leverage strategies remain reasonably stable under mild and moderate uncertainty, whereas middle-ranked strategies become more sensitive when parameter uncertainty is strong. This indicates that the main prioritization conclusion is robust, but marginal differences among strategies should be interpreted cautiously.

Table 5. Robustness and ranking-stability statistics under parameter perturbations.

Perturbation Level	Mean P (RG = True)	SD	95% CI	Spearman	Top-5 Overlap
Mild ($\pm 5\%$)	0.769	0.010	[0.749, 0.788]	0.792	0.637
Moderate ($\pm 10\%$)	0.770	0.015	[0.740, 0.799]	0.730	0.612
Strong ($\pm 20\%$)	0.768	0.026	[0.715, 0.813]	0.569	0.514

Figure 13a summarizes the average ranking agreement between the baseline ranking and perturbed rankings, confirming that ranking consistency decreases as the perturbation range expands. Figure 13b focuses on the retention frequency of the baseline Top-5 strategies. Among these strategies, RS 1-1 shows the highest retention frequency, followed by RS 3-3, RS 4-1, RS 3-2, and RS 5-1 with varying degrees of stability. This result supports the interpretation that the leading intervention domains are sufficiently stable for decision support, while the fine-grained ordering among adjacent strategies should not be over-interpreted.

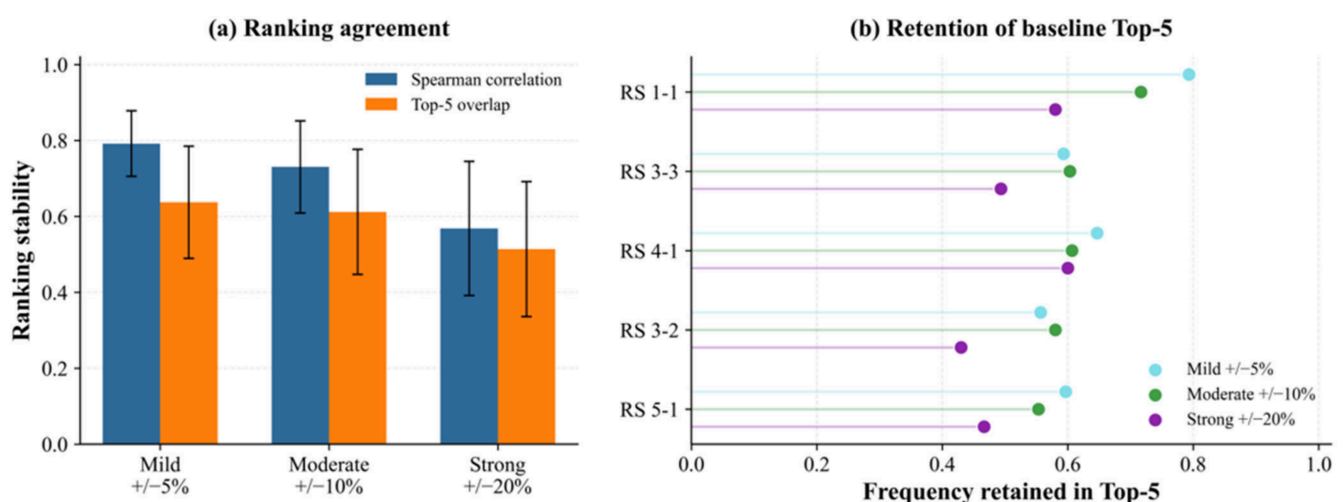


Figure 13. Strategy-ranking stability and Top-5 retention under parameter perturbations.

Figure 14a identifies the individual perturbed parameters most strongly associated with $P(\text{RG} = \text{True})$ under strong uncertainty. The most influential parameters are concentrated in the stakeholder-to-RG and gain-to-stakeholder layers, especially $P \rightarrow \text{RG}$, $O \rightarrow \text{RG}$, and $G \rightarrow \text{RG}$. Figure 14b aggregates these parameter-level associations by model layer. Stakeholder-to-RG parameters account for approximately 56% of the summed top-parameter influence, followed by gain-to-stakeholder parameters at approximately 33%. This indicates that uncertainty in the final aggregation of stakeholder-specific gains is more influential than uncertainty in individual strategy priors. The result supports the stakeholder-oriented interpretation of the framework and suggests that future applications should pay particular attention to how stakeholder gains are weighted or aggregated into system-level outcomes.

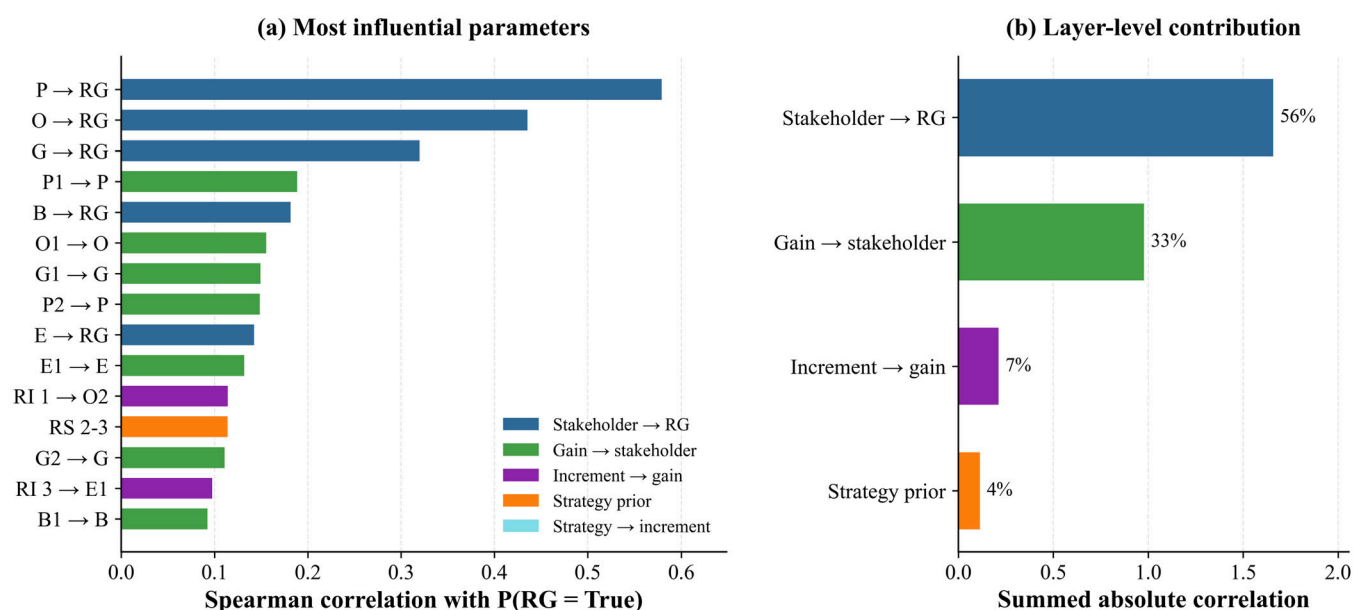


Figure 14. Layered parameter influence under strong uncertainty.

4.4.5. Comparative Analysis with Non-Evidence BN Baselines

To demonstrate the added value of the fuzzy-evidential parameterization, the proposed FEBN was compared with two non-evidence BN baselines under the same topology, node states, expert data, and inference procedure. The first baseline, termed Fuzzy-mean BN, uses triangular fuzzy numbers but aggregates expert judgments through arithmetic averaging rather than D-S evidence fusion. The second baseline, termed Crisp-mean BN, converts expert scores into crisp probabilities and aggregates them by arithmetic averaging. These baselines allow the effects of D-S evidence fusion and fuzzy-evidential treatment to be examined separately. To ensure comparability, all three models used the same expert-judgment inputs, node states, BN topology, and inference settings; only the aggregation/fusion mechanism was varied.

Figure 15a shows that the overall system-level outcome is broadly consistent across the three models. The probability of Aggregated Gain is 0.769 in the proposed FEBN, 0.786 in the Fuzzy-mean BN, and 0.763 in the Crisp-mean BN. Figure 15b compares the strategy-ranking consistency of the baseline models relative to the proposed FEBN. The Fuzzy-mean BN has a Spearman rank correlation of 0.909 and a Top-5 overlap of 1.000, while the Crisp-mean BN has a Spearman rank correlation of 0.789 and a Top-5 overlap of 0.800. Figure 15c further reports the posterior-probability differences in the target nodes relative to the proposed FEBN, indicating that the largest deviations appear in several intermediate target nodes rather than producing a major shift in Aggregated Gain. Table 6 further summarizes the key output and ranking metrics across the three models.

These results do not imply that FEBN is universally superior to simpler aggregation methods. Rather, they clarify its added value in the present study. The broad consistency in system-level outputs and strategy rankings suggests that the main prioritization results are not driven solely by the fuzzy-evidential parameterization. Compared with arithmetic averaging, the proposed FEBN preserves expert uncertainty and disagreement more explicitly through fuzzy representation and D-S evidence fusion, while maintaining strategy-prioritization results that are broadly consistent with non-evidence BN baselines. Therefore, the FEBN framework provides a transparent and uncertainty-aware basis for modeling resilience gain generation under expert-judgment uncertainty.

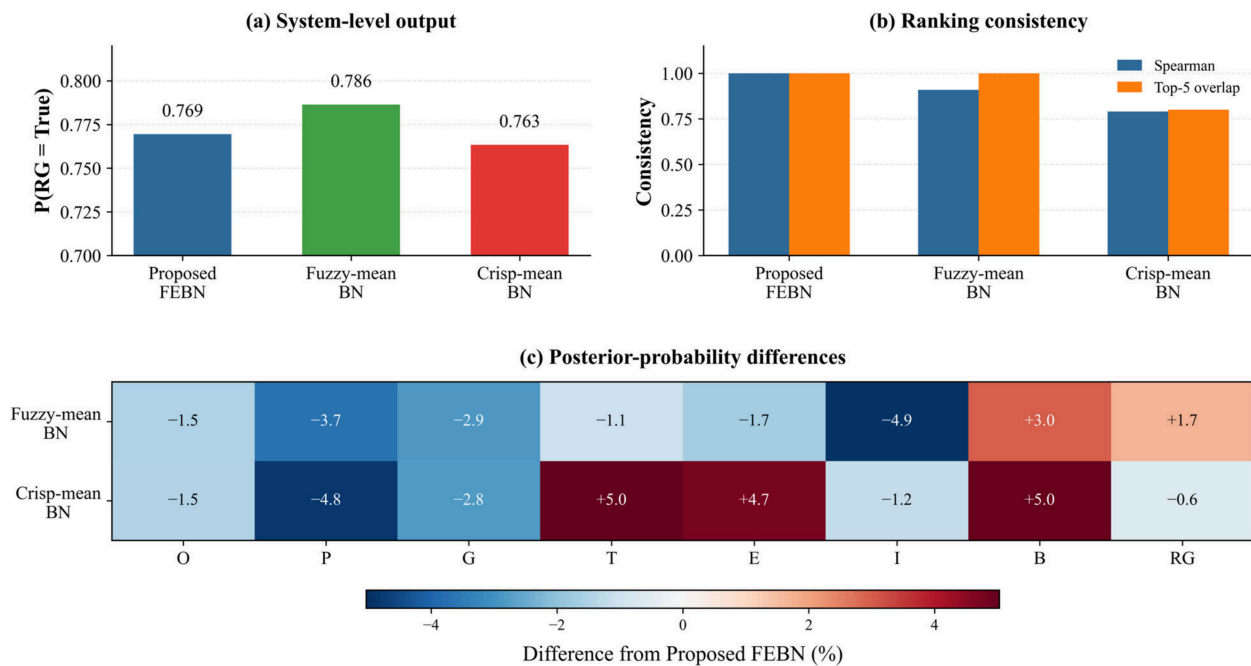


Figure 15. Comparative analysis with non-evidence BN baselines.

Table 6. Output and ranking metrics of FEBN and non-evidence BN baselines.

Model	P (RG = True)	Spearman vs. FEBN	Top-5 Overlap	Top-5 Strategies
Proposed FEBN	0.769	1.000	1.000	RS 1-1, RS 3-3, RS 4-1, RS 3-2, RS 5-1
Fuzzy-mean BN	0.786	0.909	1.000	RS 1-1, RS 3-3, RS 4-1, RS 5-1, RS 3-2
Crisp-mean BN	0.763	0.789	0.800	RS 3-3, RS 4-1, RS 3-2, RS 5-1, RS 6-1

4.5. Results of Simulating Optimization Through DBN Analysis

Following the preceding static BN analysis, a DBN analysis was performed to simulate operator-centered resilience optimization over time. Table 7 outlines the configuration of the integrated rules, representing strategy prioritization, resource constraints, and a reward-penalty mechanism. This forms a decision-making framework that mirrors real-world operational considerations. The simulation length was set to a 10-year timeframe to capture both short- and long-term system dynamics, as suggested in [5].

Table 7. Rules for simulating operator-centered optimization.

Rule	Detailed Descriptions
Strategy prioritization	Strategies are prioritized and selected based on sensitivity coefficients to node O (Gains for operator).
Resource constraints	Start with 2 strategies; Reinforcement entails increasing the prior probability of each selected strategy by 3% annually; allowed range: 1–6.
Reward–penalty mechanism	From year 3: if annual growth rate of node O increases, add one more strategy; if it declines for two consecutive years, remove one.

Table 8 presents the simulated evolution of strategy optimization. From Year 1 to Year 5, the number of reinforced strategies increases from two to six, driven by the continuous rise in node O. From Year 6 onward, the number remains at six before declining in Year 9 due to the predefined penalty mechanism. The trajectory also shows that component reliability design (RS 1-1) reaches full reinforcement after Year 5 (prior probability rises

to 100%), further confirming its importance in operator-centered optimization. Overall, these results suggest that resilience optimization in the DBN evolves as a path-dependent process shaped by strategy prioritization and resource constraints, rather than as a random accumulation of interventions.

Table 8. Operator’s strategic evolution over timesteps.

Timestep	Count	P(O)	$\Delta P(O)/\text{Baseline}$	Reinforced Strategies
1	2	74.84%	0.26%	RS 1-1, RS 5-1
2	3	75.09%	0.33%	RS 1-1, RS 5-1, RS 5-2
3	4	75.39%	0.40%	RS 1-1, RS 5-1, RS 5-2, RS 2-1
4	5	75.72%	0.44%	RS 1-1, RS 5-1, RS 5-2, RS 2-1, RS 5-3
5	6	76.08%	0.49%	RS 1-1, RS 5-1, RS 5-2, RS 2-1, RS 5-3, RS 1-2
6	6	76.34%	0.35%	RS 5-1, RS 5-2, RS 2-1, RS 5-3, RS 1-2, RS 3-3
7	6	76.59%	0.34%	RS 5-1, RS 5-2, RS 2-1, RS 5-3, RS 1-2, RS 3-3
8	6	76.80%	0.28%	RS 5-1, RS 5-2, RS 2-1, RS 5-3, RS 1-2, RS 3-3
9	5	76.95%	0.19%	RS 5-2, RS 2-1, RS 5-3, RS 1-2, RS 3-3
10	4	77.02%	0.10%	RS 5-2, RS 5-3, RS 3-3, RS 3-2

Figure 16 presents the evolution of posterior probabilities over the 10-year horizon, benchmarked against the baseline state at Year 0. It illustrates how operator-centered resilience optimization reshapes resilience stages, stakeholder groups, and gain dimensions. For clarity, the analysis focuses on stakeholder groups with strong relevance to resilience gain, involving operator (O), passenger (P), government (G), and emergency agency (E). From the simulation results, three key insights emerge.

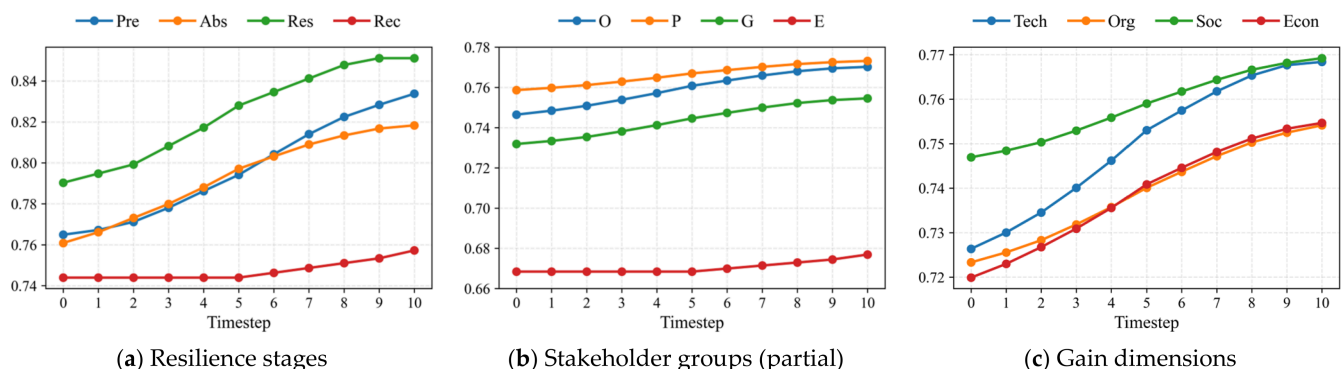


Figure 16. Evolution of posterior probabilities over timesteps.

First, operator-centered optimization tends to prioritize early- and mid-stage resilience over post-event recovery. As shown in Figure 16a, relative to the baseline state at Year 0, the posterior probabilities of Pre, Abs, and Res increase by 6.9%, 5.7%, and 6.1%, respectively, whereas Rec improves only marginally by 1.3%. This contrast reveals a structural bias in resilience investment: under resource constraints, operators tend to reinforce capabilities related to prevention, absorption, and immediate response, as these capabilities are more likely to produce visible and near-term benefits under routine disturbances. By contrast, recovery capacity becomes more critical under severe or compound disruptions, but receives comparatively less reinforcement despite its importance for long-term safety protection and loss mitigation [2]. Practically, this pattern points to a latent weakness in UMS resilience, namely the possible under-prioritization of post-disruption recovery.

Second, resilience gains are distributed asymmetrically across stakeholder groups. As illustrated in Figure 16b, operator (O), government (G), and passenger (P) exhibit steady growth, with total increases of 2.4%, 2.3%, and 1.4%, respectively. By contrast, the

emergency agency (E) shows no improvement until Year 5 and increases only marginally thereafter by 0.8%. This pattern suggests that operator-centered optimization favors gains directly associated with service continuity, regulatory compliance, and visible operational outcomes, while emergency collaboration and other gains with delayed returns receive relatively less attention [29,30]. Although the delayed improvement in E indicates that emergency and safety considerations begin to emerge in later timesteps, the overall asymmetry still suggests that resilience gains are shaped by the priorities embedded in the optimization process rather than distributed uniformly across stakeholders.

Third, technological and economic gains dominate over organizational and social ones. As shown in Figure 16c, Tech and Econ increase by 4.2% and 3.5%, respectively, exceeding Org at 3.1% and Soc at 2.2%. This pattern reflects the operator's tendency to outcomes related to system reliability and cost-effectiveness, which are more readily quantified and immediately perceived by decision-makers [12,45]. By contrast, organizational learning and social value creation depend on longer feedback loops and broader multi-actor coordination [5,21], and therefore accumulate more slowly. In practical terms, this imbalance suggests that operator-centered resilience optimization may lead to a technically efficient but socially narrower form of resilience gain, requiring continued attention to organizational and social dimensions.

5. Discussion

This section discusses the research implications and limitations. Section 5.1 elaborates the theoretical implications, Section 5.2 presents practical insights, and Section 5.3 discusses limitations and future directions.

5.1. Implications for Theory

First, this study extends the theoretical focus of resilience optimization from performance improvement to stakeholder-centered value creation. Existing infrastructure resilience studies have established mature foundations for explaining how systems withstand, adapt to, and recover from disruptions, as well as how strategies improve resilience performance [1,6,8]. However, a performance-oriented logic provides limited explanation of why resilience improvement matters to different stakeholders or how it should inform decision-making. By introducing resilience gain, this study reframes resilience not only as a system property or performance outcome [13–18], but also as a source of stakeholder-valued benefits. This connects technical resilience improvement with the interests and resource-allocation concerns of those who operate, govern, use, or are affected by infrastructure systems.

Second, this study advances the theoretical logic of resilience optimization by introducing a closed decision-feedback mechanism. Conventional resilience optimization often evaluates strategies according to their effects on system performance [2], while stakeholder interests are usually treated as external considerations after technical optimization [25]. In contrast, the proposed gain-oriented framework embeds stakeholder-specific gains within the optimization process itself, positioning them as an intermediate layer between resilience improvement and strategy prioritization. This directly responds to the research gap identified in Section 2.4, namely the lack of an explicit mechanism for integrating heterogeneous stakeholder interests into infrastructure resilience optimization.

Taken together, as illustrated in Figure 17 by the transition from “strategy→resilience” to “strategy→resilience→resilience gain”, these implications shift the resilience optimization of socio-technical infrastructure toward a gain-oriented perspective, in which resilience improvements are translated into stakeholder-valued gains and used to inform decisions.

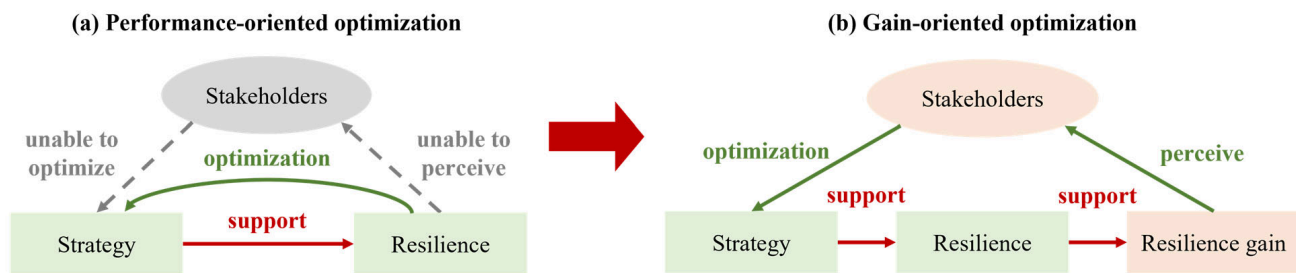


Figure 17. Paradigm transition facilitated by this study.

5.2. Implications for Practice

Practically, this study shows how gain-oriented resilience analysis can support infrastructure decision-making under resource constraints. As summarized in Figure 18, the proposed approach translates stakeholder-specific resilience gains into three practical tasks: identifying high-leverage interventions, diagnosing uneven gain distribution, and adjusting strategy prioritization over time. In the Nanjing Metro Line 7 case, resilience resources should not be spread evenly across all interventions. Priority should be given to strategies that generate broader stakeholder-valued gains, particularly component reliability design, emergency response planning, emergency resource mobilization, track intrusion protection, and fault-response recommendation. These strategies serve as practical leverage points for maintaining service continuity, reducing passenger delays, improving emergency response, and limiting disruption losses.

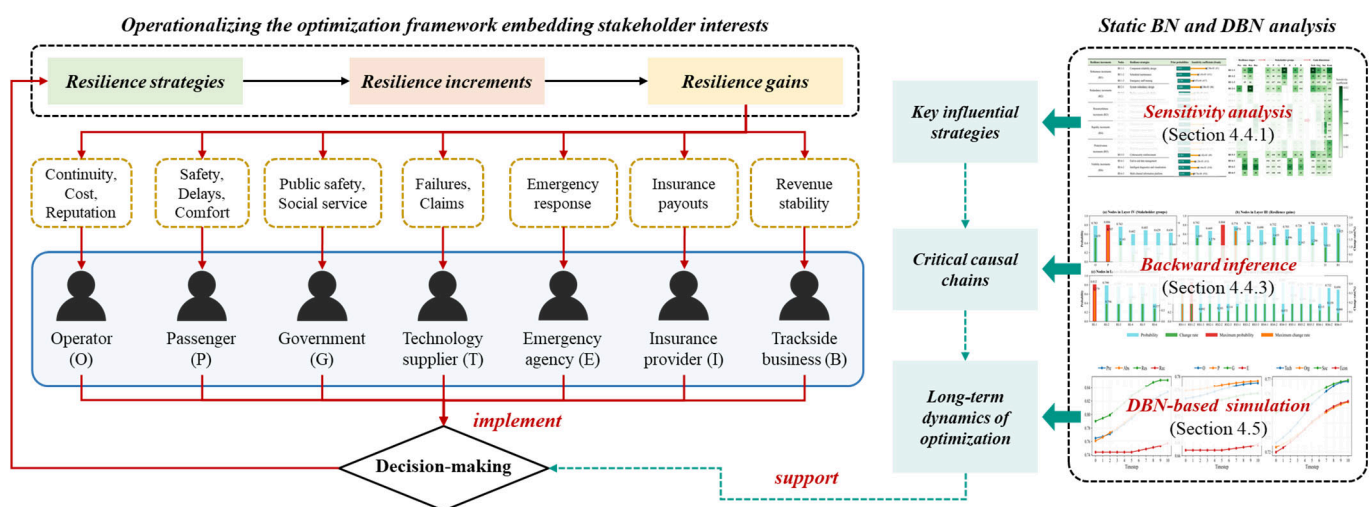


Figure 18. Synergy between the proposed decision framework and the analytical procedures.

The findings further indicate that resilience planning should consider not only which strategies perform well, but also how their gains are distributed across stages, stakeholder groups, and gain dimensions. The DBN results suggest stronger improvements in preparation, absorption, and response than in recovery, and faster growth in operator-, government-, passenger-, technological-, and economic-related gains than in emergency-agency, organizational, and social gains. This implies that resilience planning should not rely solely on operational efficiency or technical reliability indicators [5]. Public agencies and infrastructure managers should also monitor whether recovery capacity, emergency coordination, organizational learning, and social value receive sufficient investment.

The findings also offer differentiated guidance for key stakeholder groups. Metro operators can use gain-oriented results to select interventions that convert technical re-

liability into operational benefits, such as fewer service interruptions, shorter response time, and lower handling costs. Governments and emergency agencies should avoid an overly efficiency-oriented resilience agenda by setting explicit requirements for post-disruption recovery, emergency coordination, and public safety, especially under severe disruptions. Other stakeholders can also use the results to clarify indirect resilience benefits: passenger-related gains can support service-quality improvement and risk communication [29], supplier-related gains can clarify equipment accountability, insurance-related gains can inform risk-based assessment, and stabilized passenger flow can support business continuity planning for trackside businesses [47].

5.3. Limitations and Future Directions

Despite the notable theoretical and practical implications, several limitations should be acknowledged.

- (1) *Limitations in probabilistic gain mapping.* Although the proposed FEBN does not assume a deterministic or linear utility-conversion function between resilience increments and stakeholder-specific gains, its binary-state structure and Leaky Noisy-Or parameterization impose monotonic and conditionally independent parent effects. Therefore, the model cannot fully capture nonlinear gain formation, threshold effects, saturation effects, or synergistic interactions among resilience increments. In socio-technical systems, stakeholder gains may emerge only after certain capability thresholds are reached, or may increase nonlinearly when multiple resilience properties interact. Future research could extend the framework using multi-state BN, Noisy-MAX models, empirically calibrated gain functions, or hybrid BN models calibrated with operational data [1,6,48].
- (2) *Limitations in data availability and stakeholder elicitation.* Due to the confidentiality of UMS operational data, model probabilities are mainly estimated from expert judgments, which may introduce subjectivity despite their accepted use under data constraints [5]. In addition, some stakeholder interests, particularly those of passengers, suppliers, insurers, emergency agencies, and trackside businesses, were inferred from literature and expert judgment rather than direct elicitation. Future research should combine granular operational data with broader stakeholder participation to support more robust and inclusive resilience optimization.
- (3) *Limitations in DBN simulation scope.* The DBN simulation adopts an operator-centered perspective, assuming that the operator is the primary actor in implementing and reinforcing resilience strategies. However, real-world resilience optimization involves multi-actor dynamics, including government regulation, funding, emergency governance, and stakeholder coordination. Future research should incorporate multi-actor interactions to better represent stakeholder interdependencies, coordination mechanisms, and potential conflicts.
- (4) *Limitations in empirical scope and generalizability.* The empirical validation is limited to Nanjing Metro Line 7, a GoA4-level UMS with complex subsystem couplings. Although the framework is intended to be transferable to broader infrastructure systems, differences in system characteristics, regulatory environments, and stakeholder configurations may affect model structure and results. Future studies should conduct cross-case, cross-sector, and cross-national comparisons to further validate and refine the proposed framework.

6. Conclusions

This study introduced the concept of resilience gain and developed a gain-oriented infrastructure resilience optimization framework that integrates heterogeneous stake-

holder interests into strategy prioritization. Operationalized through fuzzy-evidential BN in the case of Nanjing Metro Line 7, the framework modeled the linkages among 18 resilience strategies, 6 resilience-property increments, 12 stakeholder-specific gains, and 7 stakeholder groups. By combining static BN and DBN analyses, the study demonstrates how stakeholder-specific resilience gains can be modeled, aggregated, and fed back into strategy prioritization under resource constraints. The key findings are summarized as follows.

- (1) Proactive interventions emerge as the highest-leverage strategies for improving system-level resilience gain. In particular, component reliability design (RS 1-1) and emergency response planning (RS 4-1) play leading roles, while strategy effects remain heterogeneous across resilience stages, stakeholder groups, and gain dimensions.
- (2) The main prioritization results remain broadly stable under uncertainty. Failure-scenario analysis shows that aggregated gain declines by only approximately 6%, while global parameter perturbation and comparison with non-evidence BN baselines further confirm the robustness of system-level outputs and leading strategy rankings.
- (3) Backward inference identifies robustness increments and passenger-related gains as central causal elements in achieving system-level resilience gain. The comparison between maximum posterior probability and maximum change-rate criteria further shows that critical paths differ depending on whether absolute contribution or marginal responsiveness is emphasized.
- (4) The DBN simulation reveals a structurally asymmetric pattern in long-term operator-centered optimization. It prioritizes preparation, absorption, and response over recovery, favors operator-, government-, and passenger-related gains over emergency-agency-related gains, and produces stronger technological and economic gains than organizational and social gains.

Overall, the proposed framework provides a structured and transparent approach for linking resilience strategies, performance-related increments, stakeholder-specific gains, and resource-allocation decisions. It extends infrastructure resilience optimization from a primarily performance-oriented problem toward a stakeholder-informed decision process, offering a transferable analytical basis for resilience planning in complex socio-technical infrastructure systems.

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Appendix A. Details of Data Collection

Table A1. Demographic information of the experts.

No.	Affiliation	Educational Background	Work Experience	Reason for Selection
1	Metro operating company	Postgraduate	>10 years	Long-term experience in metro operation and organizational management
2	Metro operating company	Bachelor	>10 years	Practical expertise in safety risk management and emergency response protocols
3	Metro operating company	Postgraduate	4–10 years	Operational knowledge of GoA4 system operation and management
4	Metro operating company	Bachelor	4–10 years	Technical expertise in GoA4 signaling, rolling stock, and automated subsystem management
5	Government agency	Bachelor	>10 years	Experience in urban infrastructure governance and policy enforcement.
6	Government agency	Bachelor	4–10 years	Experience in metro/transit governance and safety standards
7	Academic institution	Doctorate	>10 years	Knowledge of system resilience from the socio-technical perspective
8	Academic institution	Doctorate	4–10 years	Specialized research in infrastructure resilience and safety management

Table A2. Questionnaire for assessing Layer I-II arcs (partial: robustness dimension).

Question	Response				
	Very Low	Low	Medium	High	Very High
Likelihood of successful implementation of component reliability design (RS 1-1)					
Likelihood of successful implementation of scheduled maintenance (RS 1-2)					
Likelihood of successful implementation of emergency staff training (RS 1-3)					
Likelihood of robustness improvement under only component reliability design (RS 1-1→RI 1)					
Likelihood of robustness improvement under only scheduled maintenance (RS 1-2→RI 1)					
Likelihood of robustness improvement under only emergency staff training (RS 1-3→RI 1)					

Note: Robustness refers to a system's capability to withstand disturbances or increased demand without functional degradation. This survey focuses on technical disruptions in UMS operating at GoA4 level, as defined in the *Trial Technical and Management Standards for Urban Rail Transit Fully Automated Operation Systems*.

Table A3. Questionnaire for assessing Layer II–III arcs (partial: robustness dimension).

Question	Response					
	Very Low	Low	Medium	High	Very High	None
Fewer operational interruptions under only robustness improvement (RI 1→O1)						
Reduced handling costs under only robustness improvement (RI 1→O2)						
Improved reputation under only robustness improvement (RI 1→O3)						
Enhanced passenger safety under only robustness improvement (RI 1→P1)						
Reduced passenger delays under only robustness improvement (RI 1→P2)						
Improved passenger satisfaction under only robustness improvement (RI 1→P3)						
Enhanced public safety under only robustness improvement (RI 1→G1)						
Improved infrastructure service under only robustness improvement (RI 1→G2)						
Fewer equipment-related claims under only robustness improvement (RI 1→T1)						
Improved emergency response under only robustness improvement (RI 1→E1)						
Reduced insurance payouts under only robustness improvement (RI 1→I1)						
Stabilized commercial revenue under only robustness improvement (RI 1→B1)						

Note: Respondents were asked to assess the likelihood of each Layer III outcome (resilience gains) under the assumption that only RI-1 (robustness improvement) occurs.

Appendix B. Details of the BN Model

Table A4. Structural arcs bridging Layers II and III determined by experts.

	O1	O2	O3	P1	P2	P3	G1	G2	T1	E1	I1	B1
RI-1	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓
RI-2	✓		✓	✓	✓	✓	✓	✓			✓	✓
RI-3		✓		✓	✓	✓	✓			✓		✓
RI-4			✓	✓	✓	✓	✓			✓		✓
RI-5	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
RI-6			✓			✓		✓		✓		✓

Table A5. Causal-strength inputs for retained Layer II–III arcs.

Layer-III Nodes	Resilience Increments (Layer-II Nodes)						Leak
	RI-1	RI-2	RI-3	RI-4	RI-5	RI-6	
O1	0.520	0.480	—	—	0.500	—	0.010
O2	0.490	—	0.380	—	0.260	—	0.010
O3	0.370	0.350	—	0.380	0.390	0.290	0.010

Table A5. Cont.

Layer-III Nodes	Resilience Increments (Layer-II Nodes)						Leak
	RI-1	RI-2	RI-3	RI-4	RI-5	RI-6	
P1	0.490	0.170	0.150	0.450	0.270	—	0.010
P2	0.350	0.280	0.310	0.360	0.370	—	0.010
P3	0.280	0.180	—	0.430	—	0.400	0.010
G1	0.270	0.240	0.330	0.350	0.320	—	0.010
G2	0.430	0.450	—	—	0.310	0.058	0.010
T1	0.680	—	—	—	0.480	—	0.010
E1	0.600	0.450	0.500	—	—	—	0.010
I1	0.570	0.410	—	—	0.430	—	0.010
B1	0.270	0.110	0.180	0.220	0.290	0.360	0.010

Note: All values represent the probabilities of the “True” state under the Leaky Noisy-OR model; missing entries are shown as dashes.

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