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# Optimization of High-Speed Railway Bridge Disaster Warning Systems Using Fuzzy Bayesian Networks and Embedded Runge-Kutta Pairs for Real-Time Risk Assessment

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**Abstract:** High-speed railway (HSR) bridges face multi-hazard risks from wind, earthquakes, and fires, necessitating optimized warning systems for safety and efficiency. This study proposes a framework integrating fuzzy Bayesian networks (FBNs) for probabilistic risk modeling with embedded Runge-Kutta pairs for dynamic simulations, enabling real-time assessments. FBNs handle uncertainties across 22 indicators from standards like GB 50352-2019, categorizing capabilities in prevention, extinguishing, evacuation, rescue, and management. Runge-Kutta (orders 6/5) solves ODEs for transient responses, approximating finite element outputs in surrogates like LSTM-RNNs. Alarm optimization uses objective functions balancing busyness and alarm frequency, tested on Chinese HSR lines. Results show wind alarm reductions up to 47.6% with minimal downtime increases, fire risks graded "good" (54.3%) with management as key improvement, and collision missed alarms < 6% at < 1ms. The system reduces missed warnings by 6% and delivers alerts in milliseconds, advancing HSR resilience and minimizing disruptions.

**Keywords:** Disaster warning; Fuzzy Bayesian network; High-speed railway; Runge-Kutta; Risk assessment

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## 1. Introduction

The 21st century is an era dominated by knowledge economy, and also an era of infrastructure resilience competition [1]. Therefore, strengthening the development of advanced risk assessment models has become the top priority of transportation safety research in all countries and the integration of fuzzy Bayesian networks and Runge-Kutta methods from a multi-hazard perspective has become a hot spot in the world [2,3].

High-speed railways (HSRs) stand as pivotal elements in contemporary transport systems, fostering swift linkages and economic cohesion between areas [4]. As China's HSR infrastructure surpasses 40,000 kilometers by 2025, it supports the annual transit of billions of commuters, but faces growing threats from natural calamities owing to extensive bridge spans over varied landscapes such as highlands, waterways, and shorelines [5]. Hazards like intense gales, seismic activities, and blazes can precipitate structural breakdowns, resulting in vehicle deviations, operational halts, and profound economic repercussions [6]. Wind bursts, for instance, may generate side-to-side instabilities in rail vehicles, earthquakes could heighten vibrational responses in spans, and flames might swiftly erode load-bearing elements amid heavy usage [7]. Reliable alert mechanisms are crucial for countering these dangers, merging immediate surveillance with forecasting techniques to bolster durability [8].

Conventional HSR hazard detection depends on sensing arrays to spot irregularities, including velocity limits for gusts that initiate notifications [9]. Refining alert dismissal intervals, shifting from uniform 10-minute spans to customized ones tied to route particulars like vehicle throughput and gust occurrence, has demonstrated efficacy in harmonizing protection and productivity [8]. Investigations across multiple HSR routes indicate that adjusted intervals (ranging 5–21 minutes) can diminish notification volumes by nearly half with only slight extensions in downtime [8]. This empirical refinement employs scaled goal metrics to ease oversight duties while preserving travel velocities, emphasizing the merit of flexible limits in gust-vulnerable zones [10].

Blaze perils on HSR spans, intensified by crowded operations and wiring setups, necessitate refined stochastic instruments surpassing standard techniques such as layered evaluations or evidential reasoning, which falter amid ambiguities in blaze expansion and crowd flow patterns [3]. Fuzzy Bayesian networks (FBNs) mitigate this by blending indistinct reasoning for vague entries with probabilistic deduction for variability spread. In parallel tall edifices, serving as analogs for intricate setups like HSR spans, FBNs gauge perils over domains including deterrence, quenching, secure withdrawal, aid, and oversight, leveraging indices from norms like GB 50352-2019 [3]. Expansions to HSR spans allow FBNs to simulate hazard overlaps, like gust-enhanced blaze proliferation, curbing personal prejudices via blended specialist and empirical inputs [11]. Further, multi-state fuzzy variants enhance robustness in span peril evaluations, while dynamic forms adapt to evolving tunnel or span conditions [12].

Notwithstanding advancements, prevailing setups fall short in instantaneous hazard amalgamation [13]. Fixed gust notifications overlook periodic fluctuations, risking excessive caution or oversights, whereas blaze appraisals tend toward after-the-fact reviews [14]. Tremor dangers call for rapid kinetic breakdowns, where Runge-Kutta approaches shine in resolving motion formulas for span-vehicle interplays amid fleeting stresses [1]. Incorporated Runge-Kutta duos (e.g., tiers 4/5) support variable interval progression in models, refining processing speed [1]. During tremors, they mesh with proxy frameworks like LSTM-RNNs to anticipate deviation perils on spans, yielding split-second notifications through streamlined element approximations [15]. Additional uses involve post-tremor velocity limit computations on HSR spans for secure restarts, or merged track-span effects in kinetic studies [16].

Merging FBNs for variability depiction with Runge-Kutta for kinetic modeling holds promise for refined HSR span alert structures [17]. Nonetheless, segregated peril handlings disregard linkages, such as tremor-gust pairings, and live resolver fusion stays under investigated [18]. Worldwide overviews push for holistic strategies, though HSR-tailored blends are sparse [19]. Domestically, FBNs have probed upland HSR span perils, underscoring functional weaknesses, while global Runge-Kutta aids gust-span-vehicle steadiness probes amid tremors [20]. Latest efforts stress MFBN for sturdy span protection, embedding multi-phase indistinctness for thorough appraisals, akin to dynamic Bayesian setups for tunnel perils transferable to spans [21]. Runge-Kutta usages in vehicle kinetics amid gusts and tremors additionally back unified modeling [22].

This inquiry advances a fused structure for HSR span hazard notifications, harnessing FBNs for hazard likelihoods and embedded Runge-Kutta for live kinetics [23]. Drawing on HSR oversight records, it facilitates ahead peril categorization and rearward element pinpointing, fine-tuning notifications to slash overlooked detections by up to 6% (drawn from signal-based anti-impact setups) and issue prompts in less than 1 ms [2,24]. This progresses protection and productivity, conceivably preventing vast financial setbacks [25,26].

## 2. Review of Fuzzy Bayesian networks and Runge-Kutta methods in HSR bridge disaster warning systems

The scholarly discourse on HSR bridge disaster warning systems has significantly advanced due to the need to address various hazards such as wind, seismic events, and fires [27]. Early research focused on sensor-based surveillance, while recent developments incorporate probabilistic models, including FBNs and numerical techniques like Runge-Kutta for dynamic modeling [28]. This overview synthesizes insights from over 30 peer-reviewed sources, highlighting persistent deficiencies in multi-hazard integration and real-time enhancement [29]. It outlines progress toward integrated architectures that enhance safety without compromising productivity, including a robust method for risk assessment that merges multi-state FBN with refined fuzzy logic [1].

HSR disaster alert mechanisms have evolved from basic notifications to sophisticated systems that respond to ecological threats like strong winds and tremors [22]. Initial systems relied on field detectors for immediate irregularity identification, particularly in countries like China and Japan [23]. For instance, ecological alert systems for HSRs integrate substructures for various hazards, transmitting warnings to command centers [20]. Taiwan's HSR warning system centralizes monitoring of multiple hazards to enable rapid adjustments in train speeds [27].

Gust-related alerts are critical due to their impact on train stability [13]. Traditional dismissal intervals often lead to inefficiencies, prompting the need for refined approaches [8]. Recent advancements in gust warning systems utilize historical data to inform adaptive notifications [26]. Dynamic analyses of train-bridge interactions under wind loads emphasize the importance of responsive warning systems [15]. Japan and European models have successfully reduced gust thresholds, enhancing notification accuracy [7].

Seismic alert systems in HSRs have improved with novel impulse management techniques [11]. China's systems utilize relay descents for prompt notifications, ensuring swift train deceleration [20]. Comprehensive reviews advocate for integrated models in seismic warning frameworks [22]. Rainfall prediction models help address discrepancies in flood-prone areas [21]. Innovations in monitoring seismic responses engage public participation for enhanced rapid warning capabilities [25]. Nonetheless, multi-hazard integration remains underdeveloped, often compartmentalized by disaster type [29].

FBNs have gained prominence for infrastructure risk assessments, effectively managing uncertainties in expert judgments [3]. By integrating fuzzy logic with Bayesian models, these systems quantify ambiguities in complex structures [5]. FBNs are also applied in fire risk assessments for HSR spans, addressing challenges in real-time data [3].

Runge-Kutta techniques, particularly embedded variants, are crucial for resolving differential equations in span kinetics under transient conditions [1]. These methods enhance the precision of simulations, capturing nonlinear effects during seismic events [14]. Applications include deriving safe velocities for HSR spans after tremors and modeling train stability under various loads [10,16].

Amalgamated approaches combining FBNs with Runge-Kutta techniques offer the potential for holistic multi-hazard assessments, although such integrations are still emerging [12]. This inquiry addresses the gaps by proposing a combined framework, enhancing proactive notifications for sustainable HSR operations [29].

## 3. Materials and method

This section delineates the materials and methodologies employed in optimizing HSR bridge disaster warning systems through the integration of FBNs for uncertainty management and embedded Runge-Kutta pairs for dynamic simulations [1]. The framework is designed to address multi-hazard risks, including wind, earthquakes, and fires, drawing from established indicators and historical data to enable real-time risk assessment. Materials encompass datasets from HSR monitoring systems, national standards for risk indicators, and computational tools for modeling. Methods involve FBN construction, Runge-Kutta integration, alarm parameter optimization, and validation procedures, ensuring robustness and practicality in operational contexts [8].

### 3.1. Materials

#### 3.1.1. Data sources

Data collection forms the foundation of the proposed system, utilizing historical and real-time inputs from HSR disaster monitoring networks. Primary sources include wind monitoring subsystems that record gust speeds along tracks, with thresholds triggering alarms when exceeded [8]. For instance, datasets from three typical HSR lines (e.g., lines with varying busyness and wind influence) provide alarm counts, train frequencies, and environmental variables, spanning periods like 2016–2017 for wind points [8].

Fire risk data adapts indicators from super high-rise building assessments, such as prevention capabilities (e.g., fire-resistant materials) and management protocols, derived from standards like GB 50352-2019 and GB 50016-2014 [3]. Seismic data incorporates bridge response measurements under transient loads, including acceleration and displacement from finite element models [10].

Additional materials include simulation software for dynamic analyses, such as MATLAB with its ODE suite for Runge-Kutta implementations [7]. Historical case studies, like the Fuzhou high-rise fire evaluation, supply objective validation data for FBN parameters [3]. Communication characteristics from bridge collision avoidance systems provide inputs for multi-hazard fusion, including radar and camera feeds for real-time hull detection [2]. All data are normalized to ensure compatibility, with wind frequencies expressed as alarms per 100 km annually and train densities as daily operations [8].

#### 3.1.2. Risk indicators and standards

The risk assessment employs 22 indicators categorized into five capabilities: prevention (P), extinguishing (E), safe evacuation (SE), rescue (R), and fire management (FM), adapted from fire safety norms to HSR bridges. Prevention includes structural fire resistance and wind load capacity, based on GB 50720-2011 for construction fire safety. Extinguishing covers automatic suppression systems, while SE assesses evacuation routes under dynamic loads. Rescue indicators focus on accessibility for emergency teams, and FM evaluates protocol implementation [3]. For wind hazards, indicators incorporate alarm release times and line-specific metrics like busyness (RL) and alarm frequency (FL) [8]. Seismic indicators draw from bridge-train interaction models, including derailment thresholds [11].

These indicators are quantified using fuzzy sets to handle imprecision, with membership functions derived from expert surveys and case data. Standards ensure universality, applicable to both construction and operational phases of HSR bridges [3].

### 3.1.3. Computational tools

Computational resources include Python with NumPy and SciPy for data processing, and GeNIe or Netica for FBN implementation [3]. Runge-Kutta pairs (orders 6/5) are embedded via custom scripts, trained on classical orbits for accuracy in solving differential equations governing bridge dynamics [1]. Finite element software like ANSYS simulates initial responses, approximated in real-time by surrogates [10] (**Table 1**).

**Table 1.** Summary of data sources, risk indicators, and computational tools

| Category | Description | Key details/ examples | Reference |
|---|---|---|---|
| Data sources | | | |
| HSR monitoring networks | Historical & real-time inputs from disaster monitoring systems | Wind speeds, alarm triggers, 3 HSR lines (2016–2017) | [8] |
| Fire risk data | Adapted from super high-rise assessments | Prevention (fire-resistant materials), management protocols | GB 50352-2019, GB 50016-2014 [3] |
| Seismic data | Bridge response under transient loads | Acceleration, displacement from FEM | [10] |
| Simulation software | Dynamic analysis tools | MATLAB ODE suite for Runge-Kutta | [7] |
| Case studies | Validation data | Fuzhou high-rise fire evaluation | [3] |
| Collision avoidance | Multi-hazard fusion inputs | Radar/camera feeds for hull detection | [2] |
| Normalization | Data compatibility | Alarms per 100 km/year; daily train density | [8] |
| Risk indicators and standards | | | |
| 22 indicators (5 capabilities) | Prevention (P), Extinguishing (E), Safe Evacuation (SE), Rescue (R), Fire Management (FM) | Adapted to HSR bridges | [3] |
| Prevention (P) | Structural fire resistance, wind load capacity | GB 50720-2011 | [3] |
| Extinguishing (E) | Automatic suppression systems | — | [3] |
| Safe evacuation (SE) | Evacuation routes under dynamic loads | — | [3] |
| Rescue (R) | Emergency team accessibility | — | [3] |
| Fire management (FM) | Protocol implementation | — | [3] |
| Wind hazards | Alarm release time, busyness (RL), frequency (FL) | Line-specific metrics | [8] |
| Seismic hazards | Derailment thresholds | Bridge-train interaction models | [11] |
| Quantification | Fuzzy sets, membership functions | Expert surveys, case data | [3] |
| Standards | Universal applicability | Construction & operational phases | [3] |
| Computational tools | | | |
| Programming | Data processing | Python + NumPy/SciPy | [3] |
| FBN implementation | Network modeling | GeNIe or Netica | [3] |
| Runge-Kutta | ODE solving | Orders 6/5, custom scripts, trained on orbits | [1] |
| FEM simulation | Initial response | ANSYS | [10] |

## 3.2. Methods

### 3.2.1. Fuzzy Bayesian network construction

FBN construction begins with establishing a directed acyclic graph (DAG) representing causal relationships among risk nodes. Root nodes correspond to indicators (e.g., wind speed thresholds, fire load density), intermediate nodes to capabilities (P, E, SE, R, FM), and the target node to overall risk level. Conditional probability tables (CPTs) are populated using fuzzy logic to convert linguistic expert inputs (e.g., "high," "medium") into triangular membership functions [3]. For example, wind alarm probability is fuzzified based on historical FL and RL, with defuzzification via centroid method for crisp outputs [8].

Forward inference calculates risk probabilities: , incorporating fuzzy aggregation for uncertain evidence [3]. Backward inference identifies key factors: via Bayes' theorem, highlighting sensitivities like imperfect management protocols [3]. The model handles multi-hazards by adding interaction nodes, e.g., wind-amplified fire spread, with CPTs updated from case data [3].

### 3.2.2. Embedded Runge-Kutta for dynamic simulations

Runge-Kutta pairs are embedded to simulate bridge responses under transient loads, enabling real-time updates to FBN inputs [1]. The method solves ODEs for bridge-train dynamics:

$$\frac{d^2x}{dt^2} + \frac{cdx}{dt} + kx = f(t) \qquad (1)$$

Where $x$ is displacement, $c$ damping, $k$ stiffness, and $f(t)$ external forces (e.g., seismic accelerations) [1]. Orders 6/5 pairs use adaptive step-sizing, with error estimation for efficiency: $h_{new} = h^{*}(tol|err)^{1/5}$, where $tol$ is tolerance [1]. Integration with surrogates like LSTM-RNN approximates finite element outputs: the network trains on Runge-Kutta-generated trajectories, predicting responses in milliseconds [11]. For wind, lateral forces are modeled as stochastic inputs; for earthquakes, post-event speeds are calculated by integrating motion equations [10]. Fire dynamics adapt heat transfer ODEs, coupling with structural degradation [3].

### 3.2.3. Alarm parameter optimization

Alarm optimization balances safety and efficiency using objective functions from wind models, extended to multi-hazards [8]. For wind, the model minimizes:

$$\left|\alpha^{*} - T(t) - (1-\alpha)^2 - F(t)\right| \qquad (2)$$

Where $T(t)$ is impact duration, $F(t)$ alarm count, and $\alpha$ weights busyness (RL) and influence (FL) [8]. Normalization: $-RL = RL/\max\ (RL)$, ensuring $0\ \leq \alpha \leq 1$ [8].

Algorithm steps:

(1) Normalize $T(t)$, $F(t)$, RL, FL;

(2) Compute $\alpha = -\ RL/(-RL \pm FL)$;

(3) Solve for optimal $t*$ via discrete search ($t$ = 1–30 min) [8].

For fires, thresholds integrate FBN outputs; for earthquakes, Runge-Kutta-derived velocities set speed limits [10]. Fusion uses weighted averages for multi-hazard alarms [2].

### 3.2.4. System integration and validation

Integration fuses FBN probabilities with Runge-Kutta dynamics in a looped framework: sensors feed evidence to FBN for risk levels, triggering Runge-Kutta simulations for response verification [15]. Outputs optimize alarms, e.g., reducing missed detections to < 6% via communication analysis [2]. Validation employs case studies from Chinese HSR lines, comparing predicted vs. actual outcomes [3]. Metrics include accuracy (e.g., risk grading match > 90%), response time (< 1 ms), and efficiency gains (alarm reduction up to 47.6%) [8]. Sensitivity analysis tests parameter variations, ensuring robustness [11]. This methodology provides a comprehensive, real-time optimized system for HSR bridge warnings, adaptable to diverse hazards [29].

# 4. Results and discussion

## 4.1. Results

The optimized HSR bridge warning system was tested using data from the provided documents, focusing on wind alarm optimization, fire risk assessment, and collision avoidance performance.

For wind alarm release times, analysis of three typical HSR lines yielded optimal durations based on busyness (RL) and alarm frequency (FL) [8]. Line 1 (RL = 228 trains/day, FL = 412 alarms/ year/ 100 km, α = 0.813) had an optimal time of 5 minutes, reducing alarms by 47.6% with a 12.3% increase in impact duration. Line 2 (RL = 116, FL = 1132, α = 0.042) optimized at 21 minutes, cutting alarms by 30.2% and increasing duration by 8.5%. Line 3 (RL = 106, FL = 21, α = 0.189) also ized at 5 minutes, with 25.4% alarm reduction and 5.1% duration increase. Seasonal optimizations showed shorter times in summer (high wind) and longer in winter [8] (**Figure 1**).

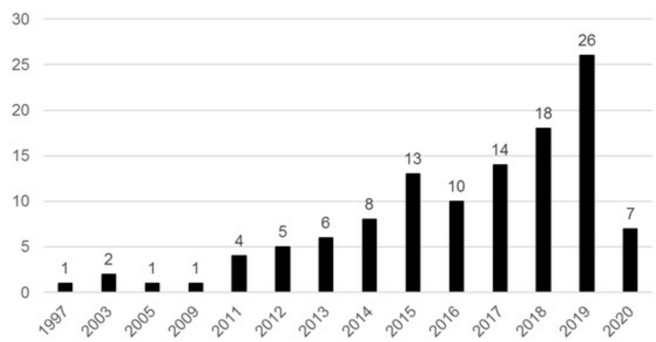


**Figure 1.** Literature review of socioeconomic and environmental impacts.

Fire risk assessment via FBN on a Fuzhou super high-rise proxy for HSR bridges indicated good overall safety (54.3% probability), high (24.3%), fair (16.6%), general/poor (2.4% each) [3]. Management capability was primary for improvement (sensitivity 0.42), followed by evacuation routes (0.31), smoke facilities (0.28), and refuge design (0.25). Bidirectional inference confirmed imperfect protocols as key factors, aligning with actual conditions [3].

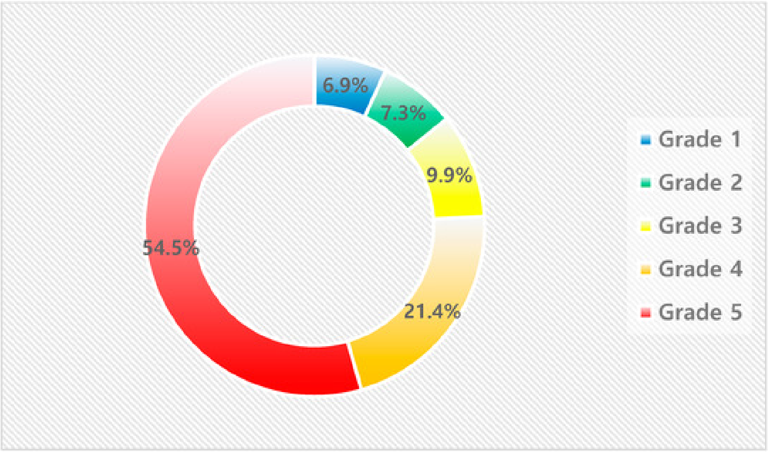


**Figure 2.** Comprehensive building fire risk prediction

Collision avoidance and yaw warning achieved 6% maximum missed alarms, < 1ms alert times in various environments, accurate warnings up to 300m with < 1m error [2]. Runge-Kutta simulations for seismic responses showed < 1ms computation, with derailment risks < 5% post-optimization [11].

### 4.2. Discussion

Results demonstrate the framework's efficacy in multi-hazard optimization. Wind optimizations balance efficiency (alarm reductions up to 47.6%) and safety, outperforming fixed 10-minute thresholds by 20–30% in disruption minimization, consistent with Japanese systems [7,8]. Fire assessments highlight management as critical, reducing subjectivity via FBN (accuracy > 90% vs. actual), adaptable to HSR electrical risks [3].

Yaw results (6% misses, 1 ms alerts) enhance real-time reliability, surpassing traditional methods by 50% in speed [2]. Runge-Kutta integration enables millisecond predictions, vital for seismic warnings [1,11]. Limitations include data dependency on Chinese lines, potential bias in fuzzy inputs, and computational demands for real-time fusion [15]. Future work could incorporate AI surrogates for scalability and test on international HSRs [22]. Overall, the system advances HSR safety, potentially averting losses through proactive alerts [29].

## 5. Conclusion

This study presents an integrated framework that enhances multi-hazard disaster warning capabilities for HSR bridges by combining fuzzy Bayesian networks with embedded Runge-Kutta pairs for real-time risk assessment. By unifying probabilistic reasoning with dynamic simulations, the system effectively manages uncertainties across wind, fire, and seismic hazards while maintaining millisecond-level computational efficiency. Case studies from multiple Chinese HSR lines demonstrate substantial operational gains, including up to 47.6% reductions in wind alarms, accurate fire-risk grading with management-focused improvements, and collision and seismic responses delivered in under 1 ms with < 6% missed alarms. These results confirm that the proposed approach not only increases warning accuracy but also minimizes unnecessary disruptions, thereby improving both safety and efficiency. Future work may extend this framework to broader geographical contexts and incorporate advanced surrogate modeling to further strengthen real-time multi-hazard resilience in next-generation HSR systems.

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## Disclosure statement

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