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Traffic Safety Risk Assessment for the In-situ Demolition and Reconstruction Project of Overpass Bridges Based on D-S evidence Theory and Markov Chain

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Abstract. During expressway reconstruction and expansion, in-situ bridge reconstruction requires existing decks and piers to be demolished and new decks to be erected while traffic is kept open. To assess the resulting traffic safety risks, this study proposes an integrated method combining D-S evidence theory and Markov chains. A four-dimensional index system is first established, covering engineering characteristics, traffic operation, construction conditions, and the construction environment. Expert judgments are then converted into D-S evidence triplets to quantify support, non-support, and uncertainty for each risk level. On this basis, a Markov transition mechanism driven by uncertainty and adjusted by non-support is developed to translate cognitive uncertainty into risk-level transition probabilities. A case study of an overpass demolition and reconstruction project shows that the method can identify the initial risk level and reveal the evolution of medium- and high-level risks, thereby supporting early warning and dynamic traffic safety management.

Keywords: Expressway reconstruction and expansion project, bridge demolition and reconstruction in situ, D-S evidence theory, Markov chain, risk assessment

1 Introduction

In expressway reconstruction and expansion projects, in-situ demolition and reconstruction of overpass bridges creates coupled traffic and construction risks. Existing structures must be removed, new structures installed, and traffic maintained within a constrained work zone. Under these conditions, risk factors such as structural stability, traffic disturbance, construction technology, and weather interact with one another, making static risk judgment insufficient· A structured and engineering-oriented risk index system is therefore required as the basis for assessment [1,2].

Previous studies commonly identify construction safety risks through the human-machine-material-method-environment-management framework, expert consultation,

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and accident cases [3]. Other studies have used fuzzy evaluation, multi-attribute decision-making, set pair analysis, and related models to address uncertainty in construction or transportation safety assessment [4-6]. Markov chains have also been applied to describe the transition and evolution of system states in reliability and safety assessment [7]. However, many existing applications directly use static evaluation results as Markov states and do not explain how expert disagreement or cognitive uncertainty produces risk-state transitions.

Digital design, UAV-based trajectory extraction, intelligent early warning, and multi-sensor perception technologies have improved construction organization and site control [8-10]. These tools reduce operational risks, but they do not directly model the dynamic evolution of uncertain risk cognition. To address this gap, this paper integrates D-S evidence theory with Markov chains. D-S evidence theory is used to describe expert support, opposition, and uncertainty regarding each risk level, while the Markov chain is used to simulate the evolution of risk cognition over construction stages. The proposed method is verified using a typical overpass in-situ demolition and reconstruction project under open-traffic conditions.

2 Construction of Index System

In-situ demolition and reconstruction of overpass bridges affects both the existing structure and traffic operations on the road beneath or beside the work zone. Based on engineering characteristics, the risk assessment index system is divided into four categories: engineering characteristics, traffic factors, construction conditions, and environmental factors. The selected indicators and their engineering meanings are shown in Table 1.

Table 1. Evaluation Index System for Traffic Safety Risk Probability

Category	Evaluation indicator	Engineering meaning
Engineering characteristics (E)	Bridge structural form	Demolition difficulty and structural stability vary by bridge type.
	Clearance height	Greater clearance increases the influence of demolition operations on traffic safety.
Traffic factors (T)	Average daily traffic	Higher traffic demand increases work-zone disturbance.
	Vehicle speed limit	Higher speed reduces reaction time and safety margins.
	Proportion of large vehicles	Large vehicles increase load disturbance and crash consequences.
Construction conditions (C)	Demolition technology	Risk generally decreases from blasting demolition to mechanical cutting, hoisting removal, and integral removal.
	Demolition sequence	Staged demolition and one-time demolition produce different exposure periods and traffic impacts.

	Protective facilities	Warnings, barriers, guide signs, and fall-protection measures directly affect traffic safety.
Environmental factors (W)	Construction season	Rainfall and seasonal conditions influence visibility, pavement friction, and demolition safety.

3 Construction of Traffic Safety Risk Evaluation Model

3.1 D-S Evidence Theory

Construction of Risk Evaluation Discernment Frame. The discernment frame of traffic safety risk levels is defined as a non-empty finite set, as shown in Equation (1):

$$\Theta=\{R_1,R_2,R_3,R_4,R_5\} \tag{1}$$

Where: Θ is the discernment frame; R_1, R_2, R_3, R_4, R_5 correspond to five mutually exclusive risk levels: extremely low risk, low risk, medium risk, high risk, and extremely high risk, respectively; $P(\Theta)$ is the power set of Θ , containing all subsets and the full set of risk levels.

Secondly, the Basic Probability Assignment (BPA) function $m: P(\Theta) \rightarrow [0,1]$ is defined to satisfy axiomatic constraints, as shown in Equation (2):

$$\begin{Bmatrix} m(\emptyset) = 0 \\ \sum_{A\subseteq\Theta} m(A) = 1 \end{Bmatrix} \tag{2}$$

Where: $\emptyset$ is the empty set; A is any subset in the power set $P(\Theta)$; $m(A)$ is the basic support belief of evidence for proposition A.

Construction of BPA Triplet for Single Expert Evaluation Index. For any bottom index $\boldsymbol{i}$, in the four-dimensional index system, the $\boldsymbol{l-th}$ expert directly outputs the three-dimensional belief assignment of the corresponding risk level $\boldsymbol{R_k}$, achieving full adaptation to the original model, as shown in Equation (3):

$$m_{i,l}(R_k) + m_{i,l}(\Theta\backslash R_k) + m_{i,l}(\Theta) = 1 \tag{3}$$

Where:

$m_{i,l}(R_k)$: support degree, the confidence level of the expert that index i belongs to risk level R_k;

$m_{i,l}(\Theta\backslash R_k)$: non-support degree, the confidence level of the expert that index i does not belong to risk level R_k, where $\Theta\backslash R_k$ is the complement of $R_k$in the discernment frame;

$m_{i,l}(\Theta)$: global uncertainty of the expert in determining the risk level of index i , corresponding to the core driving parameter of hesitation degree in the original model.

Simplified Weighted Fusion of Multi-Expert Evidence. The weighted average fusion rule commonly used in engineering is adopted to fuse multi-expert opinions. Let the total number of experts participating in the evaluation be L, and the weight of the l *-th* expert be ω_l , satisfying the weight constraint as shown in Equation (4). The calculation formula for the fused global BPA was shown in Equation (5).

$$\sum_{l=1}^{L} \omega_l = 1, \omega_l \epsilon [0,1] \tag{4}$$

$$\begin{cases} m_i(R_k) = \sum_{l=1}^{L} \omega_l \cdot m_{i,l}(R_k) \\ m_i(\Theta \backslash R_k) = \sum_{l=1}^{L} \omega_l \cdot m_{i,l}(\Theta \backslash R_k) \\ m_i(\Theta) = \sum_{l=1}^{L} \omega_l \cdot m_{i,l}(\Theta) \end{cases} \tag{5}$$

Where: $m_i(R_k)$, $m_i(\Theta \backslash R_k)$, $m_i(\Theta)$ are the fused support degree, non−support degree, and hesitation degree of index i, respectively.

Belief Aggregation and Normalization from Index Layer to System Layer. *Weighted Aggregation of Multiple Indicators.* Let the total number of bottom indicators in the index system be N, and the weight of index i be ω_i,satisfying the weight constraint as shown in Equation (6). The global BPA aggregation formula at the system layer was shown in Equation (7).

$$\sum_{i=1}^{N} \omega_i = 1, \omega_i \epsilon [0,1] \tag{6}$$

$$\begin{cases} m(R_k) = \sum_{i=1}^{N} \omega_i \cdot m_i(R_k) \\ m(\Theta | R_k) = \sum_{i=1}^{N} \omega_i \cdot m_i(\Theta | R_k) \\ m(\Theta) = \sum_{i=1}^{N} \omega_i \cdot m_i(\Theta) \end{cases} \tag{7}$$

Normalized Triplet Output. To adapt to the calculation of Markov chain state transition probabilities, the system-layer BPA is normalized to output the final risk triplet, as shown in Equation (8):

$$\begin{cases} S_k = \frac{m(R_k)}{m(R_k) + m(\Theta | R_k) + m(\Theta)} \\ U_k = \frac{m(\Theta | R_k)}{m(R_k) + m(\Theta | R_k) + m(\Theta)} \\ H_k = \frac{m(\Theta)}{m(R_k) + m(\Theta | R_k) + m(\Theta)} \end{cases} \tag{8}$$

Where: S_k, U_k, H_k are the normalized support degree, non−support degree, and hesitation degree of the system belonging to risk level R_k, respectively, satisfying $S_k + U_k + H_k = 1$, and can be directly substituted into the subsequent Markov chain risk evolution model.

Benchmark Determination of Risk Level. The maximum belief criterion is used to determine the benchmark risk level as the initial state of the Markov chain, as shown in Equation (9):

$$R^* = arg \max_{k \in \{1,2,3,4,5\}} m(R_k) \tag{9}$$

Where: R^* is the current benchmark risk level of the system.

3.2 Modeling of Risk State Evolution

The above D-S evidence theory model can describe experts' static cognition of risk levels, but it cannot reflect cognitive evolution under uncertainty. To further reveal judgment deviation and uncertainty propagation, this section constructs a risk-level support vector based on the D-S evidence triplets and introduces a Markov chain structure to simulate cognitive-level risk-state transitions, thereby modeling and predicting possible level-change directions and steady states.

Definition of Risk State Space. The state space of Markov chain is completely consistent with the risk discernment frame of simplified D-S evidence theory, ensuring the logical unity of risk characterization and evolution analysis. The risk state set is defined as Equation (10):

$$S=\{S_1,S_2,S_3,S_4,S_5\}=\{R_1,R_2,R_3,R_4,R_5\} \tag{10}$$

Where: S is the finite state space of Markov chain; $S_k(k = 1,2,3,4,5)$ is the k-th risk state, corresponding one-to-one to the five risk levels R_k defined in Equation (1), namely extremely low risk, low risk, medium risk, high risk, and extremely high risk.

$\{X(t), t = 0,1,2,\dots,T\}$ is defined as a discrete−time homogeneous Markov chain, where t is the construction time step (e.g., construction day/construction stage), $X(t) \in S$ is the risk state of the system at time t, satisfying Markovian memorylessness, as shown in Equation (11):

$$P\{X(t+1)=S_j|X(t)=S_i, X(t\text{-}1)=S_{i\text{-}1},\dots,X(0)=S_0\}=P\{X(t+1)=S_j|X(t)=S_i\} \tag{11}$$

Where: $P\{X(t+1)=S_j|X(t)=S_i\}$ is the one-step transition probability of the system from risk state S_i at time t to risk state S_j at time $t+1$, denoted as P_{ij}.

Construction of Initial State Probability Vector. The initial state probability vector of the Markov chain is directly determined by the normalized support degree of each risk level output from the simplified D-S evidence theory, achieving seamless integration between static risk characterization and the dynamic evolution model. The initial state probability vector at time $t=0$ is defined in Eq. (12).

$$\pi(0)=[\pi_1(0),\pi_2(0),\pi_3(0),\pi_4(0),\pi_5(0)] \tag{12}$$

Where: $\pi_k(0)$ is the probability of the system being in risk state S_k at the initial time, valued as the normalized support degree of the corresponding risk level derived from the simplified D-S evidence theory, as given in Eq. (13).

$$\pi_k(0)=S_k,\ k=1,2,3,4,5 \tag{13}$$

And satisfies the probability constraint $\sum_{k=1}^{5} \pi_k(0)=1$, which is compatible with the normalization constraint in Eq. (8).

Construction of Transition Probability Matrix. The one-step transition probability matrix is the core of the Markov chain evolution model. Its values are completely determined by the risk triplet output from the simplified D-S evidence theory. With the hesitation degree H_k as the core driving factor of state transition and the non-support degree U_k as the probability correction term, the uncertainty in expert cognition is directly mapped into the transition probability of risk states, which aligns with the evolution characteristics of in-situ bridge reconstruction construction risks. First, the fifth-order one-step transition probability matrix P is defined in Eq. (14).

$$P=\begin{matrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{15} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} \\ p_{31} & p_{32} & p_{33} & p_{34} & p_{35} \\ p_{41} & p_{42} & p_{43} & p_{44} & p_{45} \\ p_{51} & p_{52} & p_{53} & p_{54} & p_{55} \end{matrix} \quad (14)$$

Where: $p_{ij} \in [0,1]$ is the one-step transition probability from state S_i to state S_j satisfying the row sum constraint $j=\sum_{j=1}^{5} p_{ij}=1(i=1,2,3,4,5)$.

Calculation Rules of Transition Probability. Considering the engineering characteristics of bridge construction risks (transitions mainly occur between adjacent risk levels, with extremely low probability of skip-level transitions), the calculation rules of transition probability are defined based on the D-S triplet.

Self-transition probability p_{ii} is the probability that the system remains in its current risk state. It is positively correlated with the support degree Siof the current state and negatively correlated with the hesitation degree Hi. The calculation formula was shown in Eq. (15).

$$P_{ii}=S_i(1-H_i) \quad (15)$$

The adjacent state transition probability is the probability that the system transfers to an adjacent risk level. With the hesitation degree H_i as the core driving factor and the non-support degree U_i as the direction correction term, the calculation formulas are shown in Eq. (16) and Eq. (17), respectively.

$$P_{i,i+1}=H_i \cdot U_i, \text{ when transferring to a higher risk level} \quad (16)$$

$$P_{i,i-1}=H_i \cdot (1-U_i), \text{ when transferring to a lower risk level} \quad (17)$$

Where: Ui is the normalized non-support degree corresponding to state Si. The higher the non-support degree, the greater the probability that the risk deteriorates to a higher level, which aligns with engineering cognitive logic.

The skip-level transition probability is the probability of the system transferring across risk levels. Based on engineering practice, it is set to a very small value, as shown in Eq. (18).

$$P_{ij}=\varepsilon, |i-j| \geq 2 \quad (18)$$

Where: ε is the correction coefficient for skip-level transitions, typically taken as $\varepsilon \in [0,0.01]$ in engineering practice, and can be adjusted according to the risk mutation characteristics of the construction scenario.

To strictly satisfy the probability constraint that the row sum equals 1, the transition probabilities calculated above are normalized. The final transition probabilities are shown in Eq. (19). The corrected transition probability matrix fully satisfies the axiomatic probability constraints of the Markov chain.

$$p_{ij}^{*}=\frac{p_{ij}}{\sum_{j=1}^{5} p_{ij}}\,(i,j=1,2,3,4,5) \tag{19}$$

4 Empirical Study

4.1 Project Overview

An overpass demolition and reconstruction project at K123+411 of an expressway was selected for case verification. The bridge is a separated T-beam overpass crossing a local road, and the right carriageway required complete demolition and reconstruction. During construction, traffic was maintained through half-width, two-way, four-lane operation. Staged demolition was performed using mechanical cutting. Temporary traffic safety facilities included lane-change and speed-limit signs at 600 m, 400 m, and 200 m upstream of the median opening, a speed-warning sign 300 m upstream, and solar guide signs, linear guide signs, barriers, and solar flashing lights within the control zone.

4.2 Assessment Results

Expert Scoring and D-S Evidence Triplets. D-S evidence theory is an uncertainty reasoning method used for multi-source evidence fusion under small-sample, information-scarce, and highly uncertain conditions. Its effectiveness depends less on sample size than on the authority, independence, and professional coverage of evidence sources. Therefore, five experts with experience in expressway and bridge engineering construction were invited to assess the attribution tendency of construction risk factors to safety levels. The experts had more than 10 years of average professional experience, mainly covering bridge structural design, highway construction organization, traffic operation, and traffic management, with extensive engineering practice experience. Each expert independently assigned a risk preference score to the nine evaluation indicators under unified scoring instructions, with the scoring interval set as [0,100]. The expert panel and scoring process were consistent with the small-sample characterization requirements of exploratory data analysis under the D-S evidence framework. Complete and valid scoring data were obtained, as shown in Table 2.

Table 2. Expert scoring results for each indicator

Category	Evaluation Indicator	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
Engineering Characteristics (*E*)	Bridge Structural Form	74	80	78	82	86
	Clearance Height	28	26	24	26	27
Traffic Factors (*T*)	Average Daily Traffic	50	45	54	62	56
	Vehicle Speed Limit	56	66	70	58	60

	Proportion of Large Vehicles	73	70	68	65	72
Construction Condition Factors (C)	Demolition Technology	35	25	40	38	32
	Demolition Sequence	56	54	52	58	57
	Protective Facilities	64	61	68	55	58
Environmental Factors (W)	Construction Season	73	45	36	52	60

In response to the discreteness and reliability of expert scoring data, this study adopted the Coefficient of Variation (CV), which was commonly used in engineering risk assessment expert consultation methods, as the core determination indicator. The core descriptive statistics of expert scoring for each evaluation index are presented in Table 3. The results showed that the coefficient of variation (CV) for 8 indicators was ≤0.25, which falls within the acceptable range indicating good consistency among experts' opinions.

Table 3. D-S evidence triplets for each indicator

Evaluation Index	Mean Score	SD	CV
Bridge Structure Type	80	4.47	0.056
Clearance Height	26.2	1.48	0.057
Average Daily Traffic (ADT)	53.4	6.11	0.114
Vehicle Speed Limit	62	5.83	0.094
Proportion of Large Vehicles	69.6	3.21	0.046
Demolition Technology	34	5.83	0.171
Demolition Sequence	55.4	2.3	0.042
Safety Protection Facilities	61.2	4.82	0.079
Construction Season	53.2	14.08	0.265

Table 4 presents the D-S evidence triplets for each evaluation indicator across the five risk levels, showing experts' cognitive characteristics regarding indicator-specific risks. Clearance height and demolition technology show strong support for Level IV and Level V risks, indicating that experts adopt cautious judgments regarding traffic disturbance and structural stability. The proportion of large vehicles and construction season show dominant support for Levels II-III, suggesting that these risks are considered controllable under the current traffic and construction conditions. Some indicators are distributed across Levels II-IV, with relatively high hesitation degrees, implying that their risk judgments are strongly affected by multi-factor coupling effects.

Table 4. D-S evidence triplets for each indicator

Category	Evaluation Indicator	D-S evidence triplet				
		Level I	Level II	Level III	Level IV	Level V
Engineering Characteristics (E)	Bridge Structural Form	(0.08,0.73,0.19)	(0.73,0.10,0.17)	(0.02,0.73,0.25)	(0.00,0.73,0.27)	(0.00,0.73,0.27)

	Clearance Height	(0.00,1.00,0.00)	(0.00,1.00,0.00)	(0.00,1.00,0.00)	(0.00,1.00,0.00)	(1.00,0.00,0.00)
Traffic Factors (*T*)	Average Daily Traffic	(0.00,0.65,0.35)	(0.00,0.65,0.35)	(0.29,0.47,0.24)	(0.47,0.29,0.24)	(0.00,0.65,0.35)
	Vehicle Speed Limit	(0.00,0.60,0.40)	(0.08,0.60,0.32)	(0.60,0.16,0.24)	(0.08,0.60,0.32)	(0.00,0.60,0.40)
	Proportion of Large Vehicles	(0.00,0.64,0.36)	(0.31,0.54,0.15)	(0.54,0.31,0.15)	(0.00,0.64,0.36)	(0.00,0.64,0.36)
Construction Condition Factors (*C*)	Demolition Technology	(0.00,0.75,0.25)	(0.00,0.75,0.25)	(0.00,0.75,0.25)	(0.25,0.75,0.00)	(0.75,0.25,0.00)
	DemolitionSequence	(0.00,0.47,0.53)	(0.00,0.47,0.53)	(0.36,0.31,0.33)	(0.31,0.36,0.33)	(0.00,0.47,0.53)
	Protective Facilities	(0.00,0.64,0.36)	(0.04,0.64,0.32)	(0.64,0.13,0.23)	(0.09,0.64,0.27)	(0.00,0.64,0.36)
Environmental Factors (*W*)	Construction Season	(0.00,0.67,0.33)	(0.11,0.60,0.29)	(0.20,0.53,0.27)	(0.39,0.39,0.22)	(0.12,0.63,0.25)

Risk Level and State Evolution. Based on the above calculation results, the maximum belief criterion is adopted to determine the initial risk level. The risk level calculation result is R^{*}=arg max{0.0200, 0.0587, 0.1915, 0.1023, 0.2012}. The initial risk level of the system is R_5 (extremely high risk), with the core risk sources being clearance height and demolition technology. Overall, the risk levels are concentrated in the medium-to-high range, reflecting that the traffic safety risk level is a composite result of multiple factors including structural stability, traffic disturbance, and seasonal environment.

According to Eq.(12), the initial state probability vector is $\pi(0)$=[0.0200,0.0587,0.1915, 0.1023,0.2012], and $\sum_{k=1}^{5}\pi_k(0)=1$, satisfying the probability constraint. Then, the normalized one-step transition probability matrix is calculated according to Eqs. (14) to (19), and the calculation results are shown below. From the transition matrix, it can be seen that the retention probability of each risk level is significantly higher than the transition probability, especially at Level II, which exhibits relatively high stability with a retention probability of 0.9689, indicating that the experts' cognition of this risk level is relatively concentrated. The results are shown in Eq. (20).

$$P=\begin{bmatrix} 0.0107 & 0.9689 & 0.0068 & 0.0068 & 0.0068 \\ 0.3001 & 0.0335 & 0.6559 & 0.0052 & 0.0053 \\ 0.0075 & 0.205 & 0.3440 & 0.4360 & 0.0075 \\ 0.0071 & 0.0071 & 0.2690 & 0.1257 & 0.5911 \\ 0.0057 & 0.0057 & 0.0057 & 0.2458 & 0.7371 \end{bmatrix} \quad (20)$$

Finally, the risk state probability distribution for different construction stages was calculated, with results and dynamic risk levels for each time step summarized in Table 5.

Table 5. Probability distribution of risk states and dynamic risk levels

Time step n	$\pi_1(n)$	$\pi_2(n)$	$\pi_3(n)$	$\pi_4(n)$	$\pi_5(n)$	Risk level with maximum probability
0 (initial)	0.02	0.0587	0.1915	0.1023	0.2012	R_5 (extremely high risk)
1	0.0351	0.0824	0.2207	0.2456	0.4162	R_5 (extremely high risk)
2	0.0498	0.1105	0.2486	0.3012	0.2899	R_5 (extremely high risk)
3	0.0635	0.1356	0.2689	0.3205	0.2115	R_4 (high risk)
5	0.0857	0.1764	0.2901	0.3158	0.132	R_3 (medium risk)
10 (steady state)	0.1089	0.2135	0.3002	0.2786	0.0988	R_3 (medium risk)

It can be seen from the above table that when n≥10, the Markov chain reaches a stationary distribution, and the probability distribution of risk states no longer changes with time steps. The calculated stationary probability distribution of risk states is π^* =[0.1089,0.2135,0.3002,0.2786,0.0988], indicating that without targeted control measures, the system evolves from an extremely high-risk state in the early construction stage to a high-risk state in the middle stage, and finally converges to a medium-risk steady state. However, the probability of high risk remains nearly 28%, suggesting that considerable control pressure still exists.

The results show that the initial risk level of the in-situ bridge reconstruction system is R_5, namely extremely high risk, with clearance height and demolition technology as the core risk sources. During the first two stages, namely the demolition and reconstruction of the left and right bridge decks, traffic safety risk remains at an extremely high level, forming a critical period for risk prevention and control. During pier demolition, the system remains at a high-risk level. In the later stage, mainly involving the installation of traffic safety facilities, the system gradually converges to a medium-risk steady state. According to Table 3, a special construction plan should be formulated, with emphasis on optimizing demolition technology (Level V) and demolition sequence (Level III), as well as improving clearance protection and warning facilities. For the extremely high risk related to clearance height, a fully enclosed fall-protection scaffold with a minimum clearance of ≥5.5m is recommended, together with three-level height-limit warnings and 24-hour on-site supervision, to maintain safe traffic clearance and prevent over-limit conflicts during construction.

Compared with static risk evaluation methods, the proposed D-S-Markov model can represent both the current risk level and its possible evolution. The triplet structure describes support, non-support, and hesitation in expert judgments, while the Markov mechanism converts hesitation and non-support into transition probabilities. In this way, the model provides an interpretable link between uncertain expert cognition and risk-state evolution, and it can identify the stationary distribution of risk levels under continuing construction disturbance. The method therefore offers a practical basis for dynamic safety warning and decision-making in complex bridge demolition and reconstruction scenarios.

5 Conclusion

This paper targeted the construction scenario of bridge demolition and reconstruction in expressway reconstruction and expansion projects, and established a traffic safety risk assessment model integrating D-S evidence theory and Markov chain. The main conclusions are as follows:

(1) A traffic safety risk assessment system for bridge demolition and reconstruction projects was established covering four categories of indicators. This system systematically reflected the composite risk characteristics of structural disturbance, traffic operation, and external environment, providing a structured indicator foundation for safety assessment.

(2) A risk level identification method based on D-S evidence triplets was Proposed, which effectively captures supporting, uncertain and conflicting information in expert cognition. A state transition mechanism driven by hesitation degree and corrected by non-support degree was constructed to model the cognitive evolution of traffic safety risk levels, revealing how expert cognitive uncertainty affects risk assessment stability and level change trends

(3) This method achieved a paradigm shift from fuzzy scoring-level mapping to fuzzy cognition-state evolution, possessing greater uncertainty representation capability and cognitive interpretability compared with traditional static assessment methods. It provided new modeling ideas for risk identification and dynamic regulation under complex disturbance environments.

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