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Research Article

A Comprehensive Reliability Assessment Method for Existing Railway Bridges Based on Bayesian Theory

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The increase in traffic volume and train load poses new challenges to the reliability assessment of existing railway bridges. To construct a comprehensive assessment method for the safety and reliability of existing railway bridges, firstly, the risk factors of railway bridge structures are analyzed and the evaluation criteria are determined; secondly, based on the accident tree theory, a multilevel Bayesian network model with key points is established, and the ability of the Bayesian network bidirectional reasoning and sensitivity analysis is used to evaluate the structural safety; finally, the result was applied to the marina northern Songhua River extra-large bridge to verify the applicability of the comprehensive evaluation of the reliability of an existing railway bridge. This approach provides a theoretical basis for the maintenance and reinforcement of the Songhua River Bridge along the Bin-North Line.

1. Introduction

The reliability assessment of existing railway bridge structures is essential to ensure smooth railway lines, normal train operations, and safe travel for pedestrians. The theoretical research and practical application of a comprehensive structural condition assessment method for existing railway bridges are of great significance in accurately assessing the health of existing railway bridges and providing timely, efficient, and economical maintenance solutions, as well as diagnosing the causes of accidents after a structural failure.

At present, a certain amount of work has been carried out on bridge assessment methods. Traffic load models, corrosion degradation models, and finite element models of existing reinforced concrete bridges have been studied [1–9], and machine learning methods have been applied to the construction of structural reliability assessment frameworks [10, 11], but the amount of data required to build the models is greatly increased and does not apply to small and medium span bridges. Reliability studies on steel bridges have also been carried out gradually. The damage to steel bridges is mainly fatigue damage, and most of the studies have been conducted at the member level for the mechanical properties but not at the overall bridge level [12, 13]. In order to establish a more efficient assessment model for existing bridges, we turned our attention to Bayesian networks, which have been applied by many scholars to bridge reliability assessment [14–18], that can not only determine the state level of the bridge, but also applies the inspection data to update. However, the assessment system is not yet complete, and the assessment indexes are not perfect. Most of them focus on qualitative analysis of the reliability of bridge structure systems, and the evaluation work of railway bridges is even less advanced. The development of interdisciplinary reliability theory has brought new directions for bridge reliability assessment, carrying out a comprehensive assessment of the reliability of existing railway bridges based on a Bayesian network model, establishing a model for assessing the structural risk of railway bridges under a variety of disease factors, constructing a mathematical model of the interdependence of railway bridges as a whole, the railway bridge structure and the railway bridge components under the a priori probability of a failure of the structural components. The application of Bayesian networks can be more efficient and accurate in determining the condition of bridges and is an emerging method for bridge condition assessment.

2. Identification of Risk Factors for Existing Railway Bridges

To effectively improve the level of reliability assessment of railway bridges, the first step is to analyze the influencing factors of railway bridges in service, identify the risk factors for railway bridges, classify those risk factors, and determine their level to lay a theoretical foundation for a subsequent overall bridge reliability analysis and determination of key risk-causing factors.

2.1. Principles of Risk Factor Selection. To conduct an objective and comprehensive reliability assessment of railway bridges, the selection of indicators for assessing the risk factor status of railway bridges should abide by the following principles:

(1) Scientific: scientific means that the selected risk factors have clear concepts and scientific connotations and can describe and reflect the structural safety condition of bridges during service

(2) Representativeness: select risk factor assessment indicators that can effectively reflect the health status of a bridge in service and combine similar indicators as much as possible, generally with no more than nine subindicators

(3) Independence: the selected risk factor evaluation indexes can independently reflect a certain type of risk of a bridge structure, and the risk factor evaluation indexes of the same layer are independent of each other

(4) Feasibility: feasibility means that the selected risk factor assessment indicators can be quantitatively described through some methods

(5) Hierarchy: focused selection of different levels of risk factor assessment indicators to sort out the assessment process in an orderly and efficient manner

2.2. The Hierarchical Structure of Existing Railway Bridge Risk Factors. There are many risk factors affecting the structural reliability of existing railway bridges, and the relationship among these risk factors is intricate and complex. The condition assessment index system of bridge structures can be covered by three assessment subsystems as follows: safety, serviceability, and durability.

(1) Safety analysis: the safety of a railway bridge structure refers to the ultimate bearing capacity of the bridge structural members to resist collapse damage under the joint action of various risk factors, to avoid collapse damage to the bridge structure, and to ensure the safety of life and property.

(2) Suitability analysis: the structural serviceability of railway bridges refers to the ability to meet the requirements of the design specifications during service. The parameters include the stiffness of the main girder, the displacement of the top of the pier, and the apparent damage to the load-bearing structure and its ancillary structures.

(3) Durability analysis: the durability of railway bridge structural members refers to the ability of those members to resist a variety of deterioration processes under the combined effect of a certain service environment and certain internal factors and conditions to meet the original design service period.

2.3. Determination of Risk Factor Levels of Existing Railway Bridges. Based on the above risk factor hierarchy analysis, three subsystems of safety, serviceability, and durability were identified, and multiple risk factors were further classified by conducting a traceability analysis of each risk subsystem. If the severity of each risk factor is only evaluated as "good" or "bad," the condition of the bridge cannot be accurately described. So, the "fuzzy" theory is used to classify the risk status levels of each risk factor, not by an exact value but by a probability interval that vaguely describes the status level of the risk factor.

(1) The structural condition classes of existing railway bridges are shown in Table 1

(2) The safety status classes of existing railway bridges are shown in Table 2

(3) The applicability status classes of existing railway bridges are shown in Table 3

(4) The durability state classes of existing railway bridges are shown in Table 4

3. Existing Comprehensive Railway Bridge Reliability Evaluation Model

To predict the reliability of railway bridges and to explore the specific causes of accidents after they have occurred, a hierarchical analysis of railway bridge structures is required to establish a network model of risk factor relationships using the Bayesian network theory.

3.1. Bayesian Network Theory. Bayesian networks are mathematical representations of causal relationships between events. By integrating probability theory, fuzzy algorithms, graph theory, etc., a Bayesian network can not only provide a clear visual representation of the causal relationships between risk factors but also quantify the logical relationships between risk factors through rigorous mathematical reasoning.

Table 1: Structural condition classes of existing railway bridges.

Risk factor level	Bridge performance	Risk probability interval
I	Bridge formation status	$(0, 5\%]$
II	Affect appearance	$(5\%, 20\%]$
III	Affect use	$(20\%, 50\%]$
IV	Impact on safety	$(50\%, 80\%]$
V	Hazardous status	$(80\%, 100\%]$

3.2. Bayesian Network Structure Construction. A Bayesian network model is not built once and for all but is a continuous process of modification and improvement, requiring updated learning by the Bayesian network to achieve an accurate assessment of the reliability of railway bridges.

In Figure 1, R denotes the top event, R_1 denotes a first-level risk factor set, R_2 denotes a second-level risk factor set, R_3 denotes a third-level risk factor set, and R_4 denotes a fourth-level risk factor set. The indicators at each level contain multiple risk factor sets, and the meanings of the numbering in the incident tree model are shown in Table 5.

3.3. Parameter Determination of the Bayesian Network Model. After establishing the Bayesian network structure of an existing railway bridge, further quantitative description of the logical relationships between the nodes requires probability assignment between the nodes.

3.3.1. Root Node Prior Probability Analysis. The occurrence probability level of the root node is fuzzy and described by a probability interval. Experts evaluate the occurrence status of the root node based on the root node occurrence probability level criteria, which are shown in Table 6.

As different experts do not have the same educational background, years of experience, etc., the algebraic mean of the experts' evaluation results cannot be used directly to calculate the a priori probability of the root node, and a hierarchical analysis is needed to determine the relative weights of different experts in the survey evaluation, taking into account their educational background and titles.

After determining the occurrence probability level of the root node and the relative weight of each expert, the prior probability of the root node is calculated according to the following formula:

$$P = \sum_{i=1}^{n} \omega_i B_{ij}, \tag{1}$$

where P is the prior probability of the root node; ω_i is the relative weight of the ith expert; and B_{ij} is the central value of the probability that the first i experts consider the root node to be at j rank.

3.3.2. Nonroot Node Conditional Probability Analysis. Hierarchical analysis is used to determine the conditional probability of nonroot nodes in the Bayesian network structure of an existing railway bridge. The essence of hierarchical analysis seeks to determine the conditional probability between the nonroot nodes of the Bayesian network structure by quantitatively assessing the relative importance of one risk factor over another at the same level of risk factors. Using hierarchical analysis to determine the conditional probability table of the Bayesian network structure of an existing railway bridge has the following main steps.

(1) Construction of the Judgment Matrix. Based on the Bayesian network structure of an existing railway bridge, a judgment matrix is constructed based on the affiliation relationship between the upper and lower nodes n and the relative importance of the nodes in the same layer$A = (a_{ij})_{n\times n}$.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \tag{2}$$

where A is the judgment matrix of n nodes belonging to the same node and a_{ij} means that for the subordinate nodes, the degree of importance of node i relative to node j is a quantitative index. The judgment matrix A has the following properties:

$$\begin{aligned} a_{ij} &> 0\,(i, j = 1, 2, \cdots, n), \\ a_{ii} &= 1\,(i, j = 1, 2, \cdots, n), \\ a_{ij} &= \frac{1}{a_{ji}}\,(i, j = 1, 2, \cdots, n). \end{aligned} \tag{3}$$

The quantitative indicators of the degree of importance of the nodes in the judgment matrix are derived based on Table 7.

(2) Calculation of the Conditional Probability. To calculate the conditional probability of each node belonging to the same upper node, it is actually the calculation of the maximum $\lambda_{\max}$ eigenvalue of the judgment matrix and the solution of the corresponding eigenvector $\omega = (\omega_1, \omega_2, \cdots, \omega_n)^T$ to the maximum eigenvalue. The calculation steps are as follows.

By multiplying the row elements in the judgment matrix $A = (a_{ij})_{n\times n}$, the product vector M_i is obtained as follows:

$$M_i = \prod_{j=1}^{n} a_{ij}\,(i = 1, 2, \cdots, n). \tag{4}$$

The result b_i is obtained by opening the product vector M_i to the power as follows:

$$b_i = \sqrt[n]{M_i}\,(i = 1, 2, \cdots, n). \tag{5}$$

Standardize vectors $b_i = (b_1, b_2, \cdots, b_n)$:

$$\omega_i = \frac{b_i}{\sum_{i=1}^{n} b_i}\,(i = 1, 2, \cdots, n). \tag{6}$$

Table 2: Safety status classes of existing railway bridges.

Risk factor level	Bridge safety	Risk probability interval
I	Fully compliant with design requirements, safe	(0, 5%]
II	Basically meets the requirements, overall safety	(5%, 20%]
III	Minor damage to major components, generally safe	(20%, 50%]
IV	Defective major components requiring reinforcement or reduced functional use	(50%, 80%]
V	Not meeting safety requirements	(80%, 100%]

Table 3: Applicability status classes of existing railway bridges.

Risk rating	Bridge applicability	Probability interval
I	No apparent structural damage, functionally intact	(0, 5%]
II	Minor cosmetic damage to the structure, e.g., minor cracks	(5%, 20%]
III	Moderate damage to the structure with some impact on normal use, e.g., significant cracks, significant corrosion of reinforcing steel, etc.	(20%, 50%]
IV	Serious structural damage endangering the safety of the bridge	(50%, 80%]
V	The level of damage to the structure is too severe for further use	(80%, 100%]

Table 4: Durability state classes of existing railway bridges.

Risk factor level	Bridge durability	Risk probability interval
I	Structural elements of the bridge are intact and no deterioration of materials occurs	(0, 5%]
II	Minor defects in structural elements of the bridge, minor deterioration of materials, crack widths not exceeding limits	(5%, 20%]
III	Moderate defects in structural elements of the bridge, partial deterioration of materials, crack widths over limits	(20%, 50%]
IV	Significant defects in the structural elements of the bridge, significant deterioration of the material, and severe excess crack widths	(50%, 80%]
V	Significant defects in the structural elements of the bridge, complete deterioration of materials, crushed concrete, and fractured reinforcement	(80%, 100%]

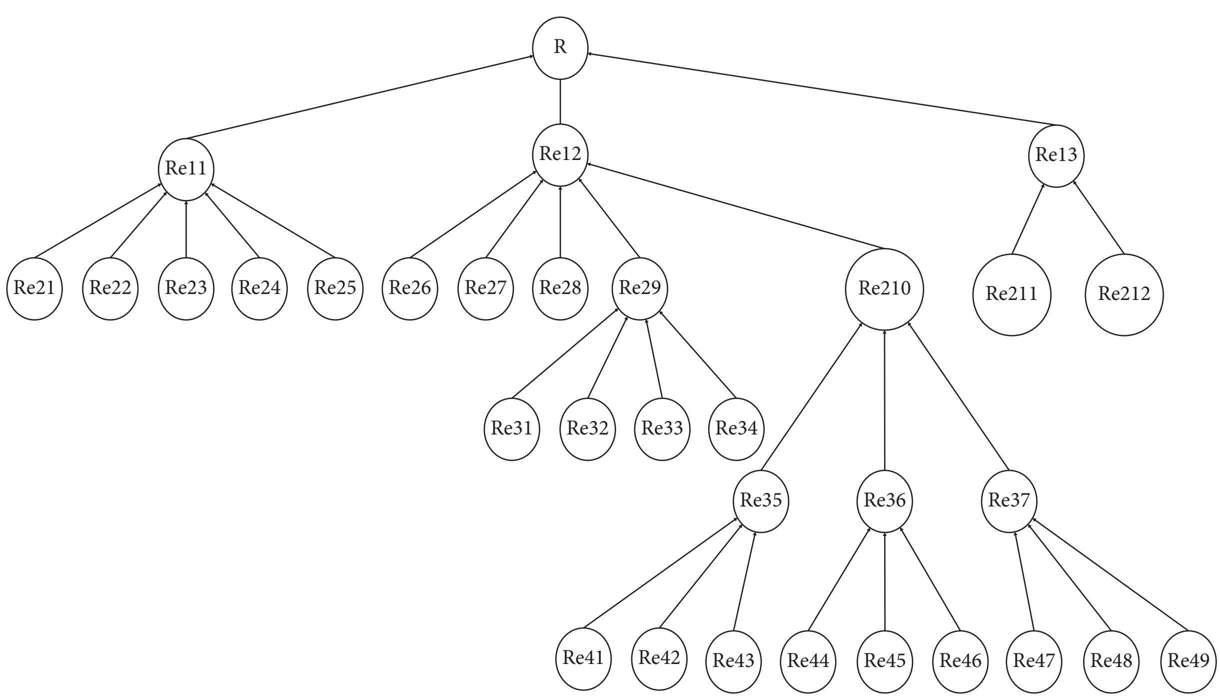

Figure 1: Bayesian network structure of existing railway bridges.

Table 5: Risk factors and numbers of existing railway bridges.

Meaning	No	Meaning	No
Security	Re_{11}	Applicability	Re_{12}
Durability	Re_{13}	—	—
Girder capacity	Re_{21}	Pier capacity	Re_{22}
Foundation capacity	Re_{23}	Support capacity	Re_{24}
Main girder fatigue	Re_{25}	Longitudinal stiffness of the main girder	Re_{26}
Lateral stiffness of the main girder	Re_{27}	The lateral amplitude of the pier top	Re_{28}
Apparent damage to load-bearing structures	Re_{29}	Apparent damage to accessory structures	Re_{210}
Girder	Re_{211}	Bridge pier	Re_{212}
Girder	Re_{31}	Pier	Re_{32}
Basis	Re_{33}	Support	Re_{34}
Floor system	Re_{35}	Affiliated facilities	Re_{36}
Others	Re_{37}	—	—
Bridge circuit	Re_{41}	Stretch	Re_{42}
Material	Re_{43}	Drainage facility	Re_{44}
Check the facilities	Re_{45}	Pavements and shelters	Re_{46}
Wing wall	Re_{47}	Slope protection	Re_{48}
River	Re_{49}	—	—

Table 6: Root node occurrence probability grade standard.

Probability rating	Probability interval	Probability center value	State description
1	$(0, 0.0003]$	0.0002	An almost impossible event during the service of a railway bridge
2	$(0.0003, 0.003]$	0.002	Less frequent incidents during the service of a railway bridge
3	$(0.003, 0.03]$	0.02	Occasional incidents during the service of a railway bridge
4	$(0.03, 0.3]$	0.2	A frequent occurrence during the service of a railway bridge
5	$(0.3, 1]$	0.9	A large number of incidents occurred during the service of a railway bridge

Table 7: Scale grade and state description.

Level of scale	State description
1	When node i is compared with node j, the quantization index of importance is 1, indicating that node i and node j are equally important
3	When node i is compared with node j, the quantization index of importance is 3, indicating that node i is slightly more important than node j
5	When node i is compared with node j, the quantization index of importance is 5, indicating that node i is significantly more important than node j
7	When node i is compared with node j, the quantization index of importance is 7, indicating that node i is more important than node j
9	When node i is compared with node j, the quantization index of importance is 9, indicating that node i is extremely important than node j
2, 4, 6, 8	When node i is compared with node j, the quantification index of importance is 2, 4, 6, or 8, indicating that node i and node j are in the middle of the above judgment
The scale grade is reciprocal	When node i is compared with node j, the quantified index of importance is a_{ij}, and when node j is compared with node i, the quantized index of importance is$a_{ji} = \frac{1}{a_{ij}}$

Calculate the maximum eigenvalue $\lambda_{\max}$ according to the eigenvector W as follows:

$$\lambda\frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{\omega_{i\max}}, \quad (7)$$

where $W = (\omega_1, \omega_2, \cdots, \omega_n)^T$ $(i = 1, 2, \cdots, n)$ is not only the eigenvector of the judgment matrix $A = (a_{ij})_{n\times n}$ but also the conditional probability distribution of the individual nodes n belonging to the same upper node. $(AW)_i$ is the first i element of vector W after multiplying matrix A with the vector.

(3) Consistency Test. Judgment matrix A is the basis of calculating the conditional probability. Therefore, it is necessary to perform a consistency test. The steps for performing a consistency test on the judgment matrix are as follows.

First, calculate the consistency indicator CI:

$$CI = \frac{\lambda_{\max}}{n-1}, \tag{8}$$

where $n$is the order of judgment matrix.

To avoid random errors, a consistency ratio CR is used to check the consistency of judgment matrix A. The calculation formula of the consistency ratio CR is shown in (11).

$$CR = \frac{CI}{RI}, \tag{9}$$

where CR is consistency ratio; CI is consistency index; RI is mean consistency index.

When consistency ratio $CR < 0.1$, it is considered that the judgment matrix meets the consistency requirement and passes the test; when consistency ratio $CR > 0.1$, it is considered that the judgment matrix does not meet the consistency requirement and cannot pass the test. Therefore, the original judgment matrix needs to be adjusted and reexamined until the consistency of the judgment matrix passes the test.

3.4. Bayesian Network Reasoning. Inference analysis using Bayesian networks is mainly based on the a priori probabilities of the nodes relevant to the nodes to be evaluated. Bayesian formulas are used to calculate the probabilities of the nodes to be evaluated and, based on the inference results, to make targeted recommendations for the repair and strengthening of a bridge structure.

3.4.1. Positive Causal Reasoning. Causal reasoning is a bottom-up reasoning process in a Bayesian network structure diagram, which calculates the occurrence probability of leaf nodes according to the joint probability of root nodes under a variety of state combinations to predict the occurrence of accidents. If Bayesian network node T has n parent nodes $X = (X_1, X_2, \cdots X_n)$ and using $T = 1$ and $T = 0$ to represent the two different states of the child node Toccurring and not occurring, then when parent node $X = (X_1, X_2, \cdots X_n)$ state combination is known, the formula for calculating the probability of occurrence of child node T is as follows:

$$\begin{aligned} &P(T = 1|X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n) \\ &= \frac{P(T = 1, X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n)}{P(X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n)} \\ &x_i \in \{1, 0\}. \end{aligned} \tag{10}$$

$P(T = 1|X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n)$is the conditional probability that the occurrence of a child node under the combination condition of the parent node states is known; $P(T = 1, X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n)$ is the joint probability of child node and parent node; $P(X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n)$ is the joint probability of the parent node.

3.4.2. Reverse Diagnostic Reasoning. Reverse diagnosis reasoning is a top-down reasoning process that calculates the probability of the root node under the condition that the state probability of a leaf node is known. Bayesian network node T has n parent nodes $X = (X_1, X_2, \cdots X_n)$, so when child node T occurs, the probability of X_i occurrence of the parent node is calculated as follows:

$$\begin{aligned} P(X_i = 1|T = 1) &= \frac{P(X_i = 1, T = 1)}{\sum_1^{2^n}\{P(T = 1|X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n) \times P(X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n)\}} \\ &= \frac{P(T = 1|X_i = 1)P(X_i = 1)}{P(T = 1)} \\ &x_i \in \{1, 0\}, \end{aligned} \tag{11}$$

where $P(X_i = 1|T = 1)$ is the posterior probability of the occurrence of the first i parent node after the occurrence of a known child node; $P(T = 1|X_i = 1)$ is the conditional probability of the occurrence of a child node under the condition that the first i parent node is known to occur; $P(X_i = 1)$ is the edge probability of the occurrence of the i parent node; $P(T = 1)$ is the probability of occurrence of a child node.

3.4.3. Sensitivity Analysis. Sensitivity analysis is an important part of the Bayesian network reasoning. When the state of a node in a Bayesian network changes, the influence degree of this node on other nodes is analyzed. If Bayesian network node T has n parent nodes $X = (X_1, X_2, \cdots X_n)$, then the sensitivity calculation formula of parent node X_i is as follows:

$$\begin{aligned} P(X_i = 1) &= \frac{\left|P(T = 1|X_i = 1) - \sum_1^{2^n}\{P(T = 1|X_1 = x_1, \cdots, X_n = x_n) \times P(X_1 = x_1, \cdots, X_n = x_n)\}\right|}{2 \times \sum_1^{2^n}\{P(T = 1|X_1 = x_1, \cdots, X_n = x_n) \times P(X_1 = x_1, \cdots, X_n = x_n)\}} \\ &+ \frac{\left|P(T = 1|X_i = 0) - \sum_1^{2^n}\{P(T = 0|X_1 = x_1, \cdots, X_n = x_n) \times P(X_1 = x_1, \cdots, X_n = x_n)\}\right|}{2 \times \sum_1^{2^n}\{P(T = 1|X_1 = x_1, \cdots, X_n = x_n) \times P(X_1 = x_1, \cdots, X_n = x_n)\}} \\ &= \frac{\left|P(T = 1|X_i = 1) - P(T = 1)\right| + \left|P(T = 1|X_i = 0) - P(T = 0)\right|}{2 \times P(T = 1)} x_i \in \{1, 0\}, \end{aligned} \tag{12}$$

where $P(T = 1|X_i = 0)$ is the conditional probability that a child node will occur if parent node i does not occur is known; $P(T = 0|X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n)$ is the conditional probability that a child node does not occur under the condition of a known combination of parent node states; $P(T = 0)$ is the probability that a child node does not occur.

4. Example Analysis of the Comprehensive Reliability Assessment for the Songhua River Special Bridge on the Bin-North Line

In this section, the reliability grade of the Bin-North Line Songhua River Bridge is evaluated using case analysis, and the feasibility and practicability of the comprehensive reliability evaluation method of an existing railway bridge based on a Bayesian network are verified.

4.1. Project Overview. The Bin-North line K2 + 660 m Songhua River special bridge is located in the Bin-North line between the Jiang-South and Jiang-North stations and is the only public railway special bridge in the Harbin Railway Bureau. The Bin-North line Songhua River special bridge is shown in Figure 2.

The K2 + 620 m Songhua River Bridge on the Bin-North Line was completed and opened to traffic from March 1932 to December 1933 by the Japan Railway Construction Bureau, and the upper highway bridge was completed and opened to traffic in August 1934. The bridge has a total length of 1065.8 m and is composed of 15 steel truss girders. Except for the 3rd to 5th holes (80 m + 96 m + 80 m), which are a set of parallel strings under Warren-type cantilevers and hanging truss girders, the other 12 holes are all 64 m parallel strings under Warren-type simply supported truss girders.

4.2. Analysis of Risk Factors for the Songhua River Special Bridge on the Bin-North Line. Through a comprehensive inspection of the bridge structure, it was found that there are various disease factors in the large bridge over the Songhua River along the waterfront and north lines. The steel truss girders are severely rusted and corroded. The connecting angles in the weak parts are cracked. The coating on the surface of some of the girders is aging and spalling. Some rivets are missing and the bolts are loose. The surfaces of the bearings of the whole bridge are rusted and corroded. The concrete of the wing walls is aging and the bottom of the wing walls has cracked corners. The conical slopes and slope protection are growing weeds and the mortar of the masonry joints is partially spalling. The concrete of the bridge piers is aging and spalling. The concrete transverse cracks exist on the top of each pier. There are water seepage and alkaline phenomenon in the piers. There are cracks in the bridge deck system, broken concrete, spalling, exposed bones, and aged and alkaline bridge deck slabs. There are deformation, blockage, and broken rubber strips in the expansion joints. There is rust and corrosion in the expansion device parts; rust and corrosion in the pavement slabs and aged bases; rust, corrosion, and deformation in the railings; blockage in the drainage facilities; and rust and corrosion in the inspection facilities.

4.3. Comprehensive Reliability Evaluation of the Songhua River Bridge along the Bin-North Line. A Bayesian network structure model was established according to the risk factors for the Songhua River Bridge along the Bin-North Line.

4.3.1. Prior Probability Calculation. To ensure the accuracy of the evaluation results, five experts with practical experience in bridge engineering were selected to evaluate the risk factors for the Songhua River Bridge on the Bin-North Line and the evaluation results of each expert based on the comprehensive consideration of their differences in education background and professional titles were weighted. The relative weights of the five experts are shown in Table 8.

Experts judged the root node probability rank in the Bayesian network based on Tables 3 and 4, and the root node prior probability was obtained by converting the Bayesian network root node probability rank judged by the experts

Figure 2: Bin-North line Songhua river bridge.

Table 8: Relative weight of the experts.

Expert no.	1	2	3	4	5
Relative weight	0.30740	0.30740	0.19629	0.10832	0.08058

into the corresponding probability centroid value and weighted average based on the weights of each expert.

4.3.2. Nonroot Node Conditional Probability Calculation. The Hierarchical analysis was used to determine the conditional probabilities of the Bayesian network structure. The Bayesian network structure model of the Songhua River Special Bridge on the Bin-North Line was analyzed as an overall bridge hierarchy model. First, a judgment matrix of the Songhua River Special Bridge system on the Bin-North Line was established, and the conditional probabilities of the Songhua River Special Bridge system on the Bin-North Line were calculated using the square root method based on the judgment matrix to obtain a table of conditional probabilities for the bridge system, quantifying the Bayesian network structure model and providing a two-way prediction and diagnostic analysis for the subsequent probabilistic support.

4.3.3. Analysis of Positive Causal Reasoning. According to the results of the positive causal reasoning analysis, the overall bridge structure failure probability for the Songhua River Bridge on the North-North Line is 21%, which affects the use of the bridge. The consequence level of the risk event is V, which is of great risk.

4.3.4. Reverse Diagnostic Analysis. By reverse diagnostic analysis result of the Songhua River Bridge, the failure probability of the whole bridge structure is 100%, the failure probability of bridge structure safety is as high as 71%, which is the main cause of the whole bridge structure failure, and the most likely cause risk chain is: (security $\longrightarrow$ the overall state of the bridge structure), so the security failure probability is adjusted to 100%. The probability of main girder fatigue events is up to 75%, and the most likely risk chain is: (main girder fatigue $\longrightarrow$ safety $\longrightarrow$ overall bridge structure state).

Table 9: Sensitivity analysis results.

Node number	Sensitive value	Node number	Sensitive value
Re_{11}	0.169	Re_{12}	0.139
Re_{13}	0.186	-	-
Re_{21}	0.300	Re_{22}	0.300
Re_{23}	0.300	Re_{24}	0.050
Re_{25}	0.050	Re_{26}	0.261
Re_{27}	0.261	Re_{28}	0.261
Re_{29}	0.266	Re_{210}	0.198
Re_{211}	0.500	Re_{212}	0.500
Re_{31}	0.300	Re_{32}	0.300
Re_{33}	0.300	Re_{34}	0.100
Re_{35}	0.292	Re_{36}	0.304
Re_{37}	0.205	—	—
Re_{41}	0.429	Re_{42}	0.143
Re_{43}	0.429	Re_{44}	0.637
Re_{45}	0.258	Re_{46}	0.105
Re_{47}	0.429	Re_{48}	0.429
Re_{49}	0.143	—	—

4.3.5. Sensitivity Analysis. Sensitivity analysis is an important part of Bayesian network reasoning. Based on backward diagnostic analysis, sensitivity analysis calculates the complete derivative set of the posterior probability distribution of risk nodes in the Bayesian network. These sensitivity values characterize the importance of the accuracy of the numerical parameters of the network for computing the posterior probability of the target. If the sensitivity value is large for a risk factor, then a small change in that risk factor may lead to a large change in the posterior of the target node. Through sensitivity analysis, the sensitivity value of each node is judged. The sensitivity analysis results are shown in Table 9.

5. Conclusions

(1) Principles for the selection of risk factors for railway bridges are proposed, and an index system including three risk subsystems for safety, serviceability, and durability is constructed

(2) The Bayesian network structure of an existing railway bridge was established, the prior probability of the root node was determined according to its occurrence probability grade standard, and the conditional probability between the nonroot nodes of the Bayesian network structure was determined using an analytic hierarchy process

(3) The existing Bayesian evaluation system for a railway bridge can be used for bidirectional reasoning and sensitivity analysis

(4) The Bayesian network model was applied to the reliability assessment of the Songhua River Bridge on the Bin-North Line to evaluate the probability of failure of each risk factor, and the evaluation results showed that the overall bridge structure failure probability of the Songhua River Bridge on the Bin-North Line is 21%

(5) The application of Bayesian networks for the creation of models for evaluation can be efficiently applied to the state evaluation of structures due to the characteristics of probabilistic graphical models that can be better visualized and greatly reduce the time required to build the models

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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