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Analysis of Structural Damage Identification Technology Based on the Bridge Truss

Zanhong Huang

School of Civil and Transportation Engineering, Guangdong University of Technology, Guangzhou, China

hzh11003836@outlook.com

Abstract. To solve the problem of accuracy and reliability of damage identification of old bridge structures, this paper compares and analyzes three damage identification methods: Bayesian update, curvature modal analysis and BP neural network. The performance comparison is carried out from the four dimensions of local damage identification accuracy, data demand and utilization efficiency, anti-interference and uncertainty quantification, and then the reliability is analyzed from the essential difference between the deterministic and uncertain methods. The analysis shows that the Bayesian updating method has more advantages in uncertainty quantification and anti-interference. The physical mechanism of curvature modal analysis is clear, which is suitable for damage location under the condition of low noise and high-density measurement points; the BP neural network relies on large-scale samples, and its generalization ability is limited. Finally, I propose that the future should focus on the research direction of "physical mechanism+data-driven" hybrid model construction, lightweight real-time monitoring technology development, and deep integration of deep learning and uncertainty quantification.

Keywords: Damage Identification, Bayesian Update, BP Neural Network, Curvature Mode, Bridge Works

1. Introduction

As the core component of transportation infrastructure, the safety of bridges is directly related to the stable operation of the social economy and the safety of people's lives and property. Especially truss structure bridge, with its excellent spanning capacity and economy, is widely used in long-span bridge engineering. However, in the process of long-term service, inevitably, material aging, structural stiffness, strength decline, and structural damage accumulation will occur, such as cracks on members, corrosion of gusset plates, or loosening of reinforcement joints and other local damage. If the damaged parts are not identified and handled in time, it will have a great impact on social security. Therefore, in recent years, various dynamic damage identification methods have become a research hotspot. Among these damage identification methods, curvature modal analysis, BP neural network, and Bayesian update method show various unique advantages and application prospects.

Although compared with some newly-built projects in recent years, the structural damage identification of bridges built early and in service for a period of time is not so noticeable, its

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importance cannot be denied. Identifying the structural damage of bridges is an important link in the operation process of bridges. In this context, the following related research work is carried out.

Curvature modal analysis is driven by a physical model, which can effectively respond to changes in local characteristics and is sensitive to changes in local stiffness. It has a good development prospect in damage identification of structural state [1]. BP neural network learns damage mode from monitoring data through nonlinear mapping, but it is greatly affected by noise and needs a large amount of data support [2]. The Bayesian update method quantifies uncertainty through the probability and statistics framework, which significantly improves the robustness of the recognition results [3]

In this paper, the three damage identification methods are systematically compared from the four dimensions of local micro damage identification accuracy, data demand and utilization efficiency, anti-interference and uncertainty quantification ability, and their reliability is analyzed based on the essential differences between deterministic methods and uncertain methods. Then combines the advantages of each method with the current technical problems and challenges to provide a theoretical reference for future research on technology optimization and innovation.

2. Literature review

2.1. Performance comparison of three damage identification methods

2.1.1. Bayesian updating method

As an uncertainty method, the fundamental advantage of Bayesian update is that it provides a probabilistic framework, which can explicitly handle and manage the uncertainty in every link from modeling to measurement. The formula is expressed as:

$$P(\theta|D)=\frac{P(D|\theta)P(\theta)}{P(D)} \tag{1}$$

"P (θ|d)" is a posterior distribution, "P (d|θ)" is a likelihood function, "P (θ)" is a prior distribution.

First, local damage identification accuracy. It is sensitive to small stiffness changes (such as stiffness loss of 5% -10%) by integrating prior knowledge and monitoring data through probabilistic inversion. For example, Yuan Minggui and others realized that the positioning error of microcracks was less than 5% in the damage identification of a steel truss bridge through a Gaussian Bayesian network (GBN) [4]. In the past decade, due to the introduction of dynamic Bayesian networks, the identification accuracy of time-series damage evolution has been further improved, and the prediction error of fatigue crack growth under variable amplitude load has been reduced by 15% -20% compared with the traditional method [5]. Its advantage is to quantify the damage confidence through the posterior probability distribution, but it has high computational complexity and relies on an accurate prior model.

Second, data demand and utilization efficiency. The data demand is moderate. It supports sequential update and fusion of multi-source data (such as static and dynamic response), and has high utilization efficiency. For example, the Bayesian sequence updating method based on multiple sets of measurements only needs 10-20 sets of data to converge.

Third, anti-interference. The noise and model error are quantized explicitly by a probabilistic framework, which has strong anti-interference ability.

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Fourth, uncertainty quantification. This is the core advantage of Bayesian method, which can provide the posterior probability distribution of parameters, so as to give the damage assessment results with confidence interval, such as "the probability of member stiffness loss is 95% between 20% and 30%" [6].

2.1.2. Curvature modal analysis

Curvature modal analysis is a deterministic method driven by a physical model. Its theoretical basis is that damage will lead to the decline of the local stiffness of the structure. According to the basic formula, when bending deformation occurs in the bridge, the sudden change of curvature mode at the damage can be obtained, and then the damage degree can be obtained [7].

First, local damage identification accuracy. This method is very sensitive to local stiffness changes in theory. Yang Zijie and other researchers have shown that the curvature mode difference mutation is obvious at the damage location, and cracks with a width of more than 0.1mm can be identified. However, this method is sensitive to the density of measurement points and noise. When the noise level exceeds 5%, the positioning accuracy decreases by about 30% [8]. Pandey et al. Used modal curvature to calculate cantilever beams and simply supported beams, and analyzed them. It was found that the change of curvature mode was almost unchanged outside the damage area, and was limited to the vicinity of the damage area. Using this property, the damage area of the structure can also be calculated [9].

Second, data demand and utilization efficiency. A high-density sensor network is required to obtain complete modal data, and multiple modal tests are required, so the cost of data acquisition is high. Bai Lushuai et al. Pointed out that the method needs to re-decompose the overall stiffness matrix for each damage identification, and the calculation efficiency is low [10]. The research of Xu Feihong et al. Shows that the requirement of measuring point density can be reduced to a certain extent, but the computational complexity will increase [11] through polynomial curve fitting and optimization of vibration mode data.

Third, anti-interference. It is sensitive to the test noise, and the noise makes it easy to mask the modal changes caused by small damage. Bao Longsheng and other experiments show that 5% noise can increase the false alarm rate of the curvature mode difference method to 40% [12].

Fourth, uncertainty quantification. Both curvature modal analysis and BP neural network are deterministic methods, which output a single damage index and cannot quantify the uncertainty. Although the error can be counted through repeated tests, it is not an internal probability framework [8].

2.1.3. BP neural network method

BP neural network belongs to a data-driven method. The traditional BP network is a deterministic model, but the Bayesian neural network developed in recent years gives it the ability of uncertainty quantification, which can be regarded as a hybrid method.

First, local damage identification accuracy. The damage mode is learned from the data through nonlinear mapping, and the improved BP network has high recognition accuracy for multiple damage conditions (the fitting degree between the predicted value and the real value is 0.97) [12,13]. However, Li Xueliang and others pointed out through research that BP neural network relies on a large number of label data to identify the damage location accurately, while the identification error of damage degree is large, and the traditional BP network cannot quantify the uncertainty [14].

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Second, data demand and utilization efficiency. Relying on large-scale labeled data sets (such as thousands of damage samples), the training is time-consuming and requires high-performance computing power. Although the dimension reduction technology is introduced into the improved BP network, the complexity of data preprocessing is still high [13].

Third, anti-interference. Anti-jamming depends on the representativeness of training data. If the training set contains noise samples, the network has certain robustness; But the generalization ability of unknown noise modes is weak [13].

2.2. Reliability analysis of three methods

2.2.1. Deterministic method (curvature modal analysis, BP neural network)

Under ideal conditions (low noise, complete data), the reliability of deterministic methods is high, but in practical engineering, due to environmental variation, model error, load uncertainty, and other factors, its reliability is significantly reduced, and this decline in reliability has significant nonlinearity and unpredictability.

For curvature modal analysis, its reliability bottleneck mainly stems from the difference between the physical model and the actual structure, and the uncontrollability of environmental interference. Under ideal conditions, the coincidence between the curvature mode calculated by the accurate finite element model and the measured value can reach more than 95%, but in the actual bridge, the non-uniformity of material parameters, the nonlinearity of node connection and other factors will lead to the model error, which will expand the damage identification error of curvature mode to 20%-30% [7]. Temperature change is the key environmental factor affecting its reliability. In areas with significant seasonal temperature changes, the thermal expansion and cold contraction of bridge structures will lead to systematic drift of modal parameters, which is difficult to distinguish from the modal changes caused by damage, leading to miscalculation. In addition, the rationality of the layout of measuring points directly affects the data integrity. If the density of measuring points is insufficient, it will lead to the interpolation error of the vibration mode and further reduce the recognition reliability.

The reliability of the BP neural network mainly depends on the quality and representativeness of the training data set. Under the ideal conditions of comprehensive training set coverage and controllable noise level, its damage identification accuracy can exceed 90%, but the limitations of training data in practical engineering will seriously restrict its reliability [12]. On the one hand, the damage modes of actual bridges are diverse and random, and the training set is difficult to cover all possible damage conditions. When there are uncovered damage modes, the network is prone to misjudgment or missed judgment. On the other hand, the distribution difference between training data and actual monitoring data will lead to the decline of the model generalization ability. In addition, the "black box" characteristic of BP neural networks makes its reliability verification difficult, and it is unable to identify the error source and confidence level of the results, which brings risks to engineering decision-making.

The reliability of the deterministic method is also significantly affected by the accuracy of the monitoring system. The measurement error of the sensor and the signal attenuation in the process of data transmission will lead to the distortion of the input data, and then affect the recognition results.

2.2.2. Uncertainty method (Bayesian update)

Bayesian updating method describes cognitive uncertainty (such as uncertainty of model parameters) and random uncertainty (such as measurement noise and load fluctuation) through probability distribution, and can explicitly quantify the impact of various uncertainties on identification results, so its reliability is more robust, traceable and interpretable [13].

The reliability of the Bayesian updating method is first reflected in its ability to deal with model uncertainty. By integrating the prior distribution with the engineering experience and existing research results, and then updating the posterior distribution combined with the measured data, the error caused by model simplification and assumptions can be effectively reduced. For the measurement uncertainty, the Bayesian updating method models the measurement noise through the likelihood function, which can effectively separate the noise signal and damage characteristic signal, and maintain high recognition reliability even in the case of large measurement noise.

The reliability of the Bayesian updating method is also reflected in its sequence updating ability. With the continuous accumulation of monitoring data, the posterior distribution can be continuously optimized through sequence updating, so that the identification results gradually converge to the real value, and the reliability of long-term monitoring can be significantly improved.

There are also some constraints on the reliability of Bayesian updating methods, including the rationality of the prior distribution and computational complexity. If the prior distribution is improperly selected, the posterior distribution may deviate from the true value, affecting the recognition reliability. The complex probability calculation may lead to a lack of real-time performance, which makes it difficult to meet the needs of rapid monitoring. In recent years, with the development of efficient algorithms such as subset simulation and Markov chain Monte Carlo (MCMC), the computational complexity problem has been effectively alleviated, making the real-time application of the Bayesian update method possible.

3. Suggestions for future research

First, information fusion and hybrid methods: the future trend is to integrate different methods and learn from each other. For example, taking physical sensitive indicators such as curvature mode as the observation data updated by Bayes or the input characteristics of a neural network, a hybrid model of "physical mechanism+data driven" is constructed [15,16]. Previous studies have attempted to use curvature mode as input to establish nonlinear mapping with damage location and degree using a neural network, while Bayesian framework can well integrate multi-source information such as dynamic and static response vectors [6,17].

Second, lightweight and real-time monitoring: with the development of edge computing, it will be an important way to promote the wide application of structural health monitoring technology to develop a lightweight model with higher computational efficiency, so that it can be deployed on embedded monitoring equipment to realize real-time online damage identification and early warning [16].

Third, the deep integration of deep learning and uncertainty quantification: the development of deep learning models with inherent uncertainty quantification capabilities, such as Bayesian neural networks, is an important direction [18]. This kind of model can not only give the prediction results, but also provide the uncertainty measurement of the results, which is very important for engineering risk assessment

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4. Conclusion

Through multi-dimensional comparison and reliability analysis, this paper systematically clarifies the core advantages and applicable boundaries of three bridge damage identification methods: Bayesian update, curvature modal analysis and BP neural network. Based on different technical logics, the three types of methods have formed differentiated performance characteristics: Bayesian update relies on the probabilistic statistical framework, which is outstanding in terms of quantitative uncertainty and anti-interference, and can provide quantitative risk information for engineering decision-making, which is suitable for long-term safety monitoring with high reliability requirements; Supported by clear structural mechanics mechanism, curvature modal analysis is highly sensitive to local stiffness changes. Under the condition of low noise interference and high-density measurement point layout, it can achieve accurate damage location, which is suitable for phased damage detection of small and medium span bridges. With the ability of nonlinear mapping, the BP neural network can realize rapid identification in the scene with sufficient data samples and clear damage patterns. However, due to the data dependence and "black box" characteristics, its generalization ability and reliability are easily restricted by the sample quality and environmental interference. There are obvious limitations in the application of the BP neural network in complex engineering scenes without targeted annotation samples. Future research should focus on the integration and optimization of the three methods, combined with lightweight model development and multi-source information fusion technology, to break through the bottleneck of computational efficiency of traditional methods, promote the engineering application of real-time online damage early warning, and improve the accuracy, reliability and reliability of bridge damage identification, to provide strong technical support for the use safety and health monitoring of bridges.

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