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Analyzing Performance Evolution of In-Service Bridge Structures Based on Fusion of Multi-Source Sensing Data and Digital Twin Models

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Abstract. As China's large number of bridges enter the mid-to-late stages of their service life, accurately assessing their structural performance and predicting trends of deterioration have become central challenges in operations and maintenance management. Traditional inspection methods rely on periodic manual inspections or offline data analysis, which cannot effectively reflect the real-time state of structures under complex environmental conditions and vehicle load interactions. Therefore, this paper proposes an in-service bridge structural performance evaluation framework based on digital twin technology. First, high-precision geometric models of bridges are established using oblique photogrammetry and BIM technology. Real-time response data such as strain and deflection are obtained through deployed fiber Bragg grating and acceleration sensor networks. A hybrid model combining physical mechanisms and data-driven approaches is then constructed, and the CNN-PSO deep learning algorithm is used to modify finite element model parameters, realizing virtual-real mapping and synchronous mapping. Finally, a long short-term memory network is combined to predict the degradation trend of bridge bearing capacity. Experimental results show that the proposed method can control the bearing capacity evaluation error within 5% and provide early warning of stiffness degradation trends, supporting decision-making for preventive bridge maintenance.

Keywords: Digital Twin, Bridge Engineering, Broussonetia Papyrifera Health Monitoring, CNN-PSO Correction Algorithm, Bearing Capacity Assessment

1. Introduction

Bridges are a key part of the transportation system, and their safe operation is critical to people's lives, property, and the smooth flow of regional economic activities. However, after long-term service, bridges gradually suffer from performance degradation due to natural material aging, overloading caused by increasing traffic volume, and continuous erosion from environmental factors such as wind, rain, and freeze-thaw cycles.

At present, bridge operation and maintenance mainly rely on codes, regular manual inspections, and load tests. This approach is essentially a "periodic checkup," which has obvious drawbacks such as poor timeliness and high cost. Moreover, it is difficult to detect early damage inside or in hidden

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parts of the structure. Problems are often only identified after they have worsened, missing the best window for maintenance.

In recent years, structural health monitoring systems have been widely used, with various sensors installed on bridges to collect massive amounts of response data. Yet these data often fail to reflect the real state and mechanical behavior of the physical structure. Due to the lack of efficient data fusion and in-depth analysis mechanisms, we end up with abundant data but insufficient useful information.

Digital twin technology has brought a revolutionary way to link real bridges with their virtual models. By building an accurate digital copy and updating it constantly with real-time sensor readings, the twin can reflect, analyze and predict how the actual bridge will perform over its entire life. This work aims to develop such a digital twin that faithfully shows the bridge's real-time structural behavior and forecasts its future condition. It integrates different kinds of sensor data with high-precision engineering models and uses deep learning to improve accuracy and predict performance changes. This effectively solves the long-standing problem of mismatched monitoring data, analysis models and maintenance decisions. The research offers reliable support for more scientific, targeted and preventive bridge maintenance.

2. Digital twin model construction and data fusion

2.1. Geometric model construction of digital twin

Building high-fidelity geometric models is the foundation of digital twins. In this paper, high-precision 3D point cloud data of bridges is obtained using UAV oblique photogrammetry, combined with aerial triangulation and dense point cloud generation algorithms. Such point cloud data can accurately reflect the actual geometric morphology of existing bridges, including potential deformations and deflections. Subsequently, the point cloud data is registered with the design drawings and the initial BIM model of the bridge. Precise alignment between the point cloud model and the BIM model is realized via feature point extraction and the iterative closest point algorithm. On this basis, reverse modeling technology is adopted to modify and reconstruct local structural components with deviations, such as support settlement and beam deformation regions. Finally, a high-fidelity virtual geometric model highly consistent with the actual bridge in geometric dimensions and spatial positions is constructed. Based on laser radar point cloud data, accurate extraction of bridge components is implemented. The average precision, recall rate and F1-score of pier points reach 99.70%, 93.20% and 96.22% respectively [1].

2.2. Multi-source heterogeneous data acquisition and transmission

To fully monitor the mechanical performance and service environment of bridges, a multi-source heterogeneous sensor system is installed at key positions of the bridge. The system mainly includes distributed optical fiber sensors arranged along the main girder, which expand the sparsely measured deflection data into a continuous deformation field of the entire bridge [2]. Accelerometers are placed at critical sections such as the main girder and bridge tower to obtain the overall vibration characteristics of the bridge. Deflection gauges are installed at mid-span and supports to measure alignment changes of key sections. Meanwhile, temperature and humidity sensors are used to monitor the influence of environmental factors on structural responses.

On-site, raw data collected by sensors is gathered by data acquisition instruments and preprocessed at the edge side, including filtering and denoising, abnormal value correction, and time

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synchronization of multi-source data. To support real-time data transmission between the physical bridge and the digital twin model, the processed data is uploaded to a cloud server or local server using the MQTT protocol [3]. As a data subscriber, the digital twin platform receives and parses the data in real time and uses it as real-time state inputs to drive the virtual model.

2.3. Hybrid model correction method based on deep learning

2.3.1. Limitations of traditional finite element model correction methods

Traditional finite element model correction is usually based on sensitivity analysis, adjusting material parameters (such as elastic modulus) or boundary conditions (such as constraint stiffness) manually so that the model output (such as frequency, displacement) approaches actual measurements. When dealing with complex bridge structures and high-dimensional parameters, this method involves huge computational costs and is prone to falling into local optima, making it difficult to achieve online automated calibration and failing to meet the real-time requirements of digital twins.

2.3.2. Parameter inversion combining convolutional neural networks and particle swarm optimization

To solve the above problems, this paper presents a simple hybrid correction method based on deep learning. Its main idea is to build a data-driven model instead of complex and time-consuming finite element calculations. First, we use the original finite element model to run a large number of simulations within the parameter range, generate a large number of strain time-history data, and match them with corresponding material parameters (such as stiffness reduction coefficients) and boundary conditions to form a training dataset. In practical use, we input the measured strain data into the trained CNN model to quickly obtain a set of preliminary estimated parameters. To improve accuracy further, these estimated values are input into a physics-informed convolutional neural network (PICN). By considering temperature factors such as solar radiation, mountain shading and weather changes, this model can accurately reflect the uneven temperature distribution on the bridge surface in both time and space [4]. These results are then used as the initial values for the particle swarm optimization (PSO) algorithm. With the goal of minimizing the difference between calculated deflection and measured deflection, the algorithm performs a detailed search near the parameters, and finally identifies the boundary conditions and material degradation degree that best match the actual structural state.

2.3.3. Virtual-real error backpropagation and model self-calibration

To adapt to the gradual changes in bridge conditions over time, a continuous feedback mechanism is established between the virtual digital model and the actual structure. During regular service, the digital twin platform compares real-time measured bridge deflection with model-calculated values. When the deviation between them becomes significant and exceeds a predefined threshold, the system automatically triggers an online self-tuning procedure. The CNN-PSO module is adopted to recompute the latest structural parameters, and the key data within the finite element model is updated accordingly. This forms a dynamic closed loop driven by real structural measurements, ensuring that the digital twin model remains consistent with the current actual state of the bridge at all times.

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3. Structural performance evolution analysis and deterioration prediction

3.1. Real-time assessment of bearing capacity based on digital twin

After dynamic correction, the mechanical behavior of the digital twin model is highly consistent with that of the actual bridge. On this basis, virtual loading tests can be directly carried out on the model to simulate the structural response under design load combinations. By extracting key indicators from the model calculation results, such as internal forces, stress distribution and deflection of critical sections, the bearing capacity of the bridge under its current condition can be evaluated in real time in accordance with existing bridge evaluation specifications. Compared with traditional evaluation methods based on simplified formulas or regular inspections, the proposed approach takes into account the actual stiffness degradation and complex boundary conditions of the current structure, leading to more accurate evaluation results.

3.2. Structural response simulation under fatigue loads and extreme conditions

The value of the digital twin model lies not only in evaluating the current state, but also in predicting future performance. Based on typical vehicle load spectra and environmental load spectra obtained from statistical analysis of historical monitoring data, fatigue loads that may be encountered in the future can be applied to the digital twin model. Through simulating millions of vehicle passages, the fatigue damage accumulation process of the structure can be analyzed. At the same time, extreme events can be simulated, such as once-in-a-century wind loads, seismic loads, or scenarios involving overweight vehicles, to evaluate the safety margin of the bridge under extreme conditions and provide a basis for emergency response plans.

3.3. Stiffness deterioration trend prediction based on LSTM network

To further achieve preventive maintenance, this paper introduces Long Short-Term Memory (LSTM) into Recurrent Neural Networks (RNN) to complete the long-term trend prediction of performance degradation. LSTM networks excel at processing time-series data and can learn the long-term dependencies hidden within historical monitoring data. LSTM networks can address the limitations of RNNs, which rely heavily on weight initialization strategies and appropriate optimization algorithms [5]. Processed long-term monitoring data, including fundamental frequency reflecting overall structural stiffness and strain amplitude characterizing local damage, are adopted as input features, while the bearing capacity or deflection over a future period is set as the output label for training the LSTM prediction model. The well-trained model enables probabilistic forecasting of the evolutionary trends in bridge bearing capacity and maximum deflection over the next 3 to 5 years. If the prediction indicates that an indicator is approaching its warning threshold, the system will automatically issue an alert to remind managers to carry out preventive maintenance or reinforcement at an appropriate time. In this way, structural damage can be avoided and the service life of the bridge can be effectively prolonged.

4. Experiment verification and result analysis

As bridge projects are getting bigger and their structures are turning more and more complicated. Traditional finite element model correction methods have obvious drawbacks, like slow calculation speed and poor convergence. Taking the typical long-span bridge, Xinghai Bay Cross-Sea Bridge, as the research object, this chapter puts forward an optimized finite element model updating method

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based on the CNN-PSO hybrid algorithm. This method makes full use of the fast feature extraction advantage of deep learning and the global search capability of intelligent optimization algorithms, so as to adjust model parameters efficiently and accurately.

4.1. Introduction to engineering case and monitoring system deployment

Xinghai Bay Cross-Sea Bridge is a key transportation hub that links the central urban area of Dalian with its southern coastal new district. The main bridge is a double-pylon, double-cable-plane steel box girder cable-stayed bridge, with a span layout of (90 + 180 + 90) meters. It is designed to meet the Highway-I load standard, and the designed driving speed is 60 kilometers per hour.

The bridge's health monitoring system is equipped with 32 acceleration sensors and 48 strain sensors in total, and the sampling frequency of these sensors is set at 100 Hz. Data simulated according to the structural characteristics and span layout of Xinghai Bay Bridge are used as the research basis, with reference to the Benchmark standard model proposed by the Structural Health Monitoring Committee of the American Society of Civil Engineers (ASCE) [6]. These data cover structural responses under various conditions including different traffic volumes, temperature variations, and wind loads.

4.2. Verification of model updating effectiveness

The initial finite element model built based on design drawings does not consider material aging and boundary condition degradation. Calculation results show that the theoretical maximum deflection of the mid-span section is 21.5 mm, whereas the measured maximum deflection is 28.3 mm, with an initial deviation of 23.8%, failing to meet assessment accuracy requirements.

The hybrid model updating process inputs the measured acceleration and strain time-series data into the trained CNN model to quickly invert and obtain initial parameters (e.g., concrete elastic modulus reduction factor of 0.82, pier stiffness reduction factor of 0.75).

These parameters are used as the initial swarm for the PSO algorithm to perform a fine search within the parameter domain.

After 15 iterations, the algorithm converges. The deflection time-history curve output by the corrected digital twin model closely matches the measured curve.

The figure 1 illustrate that After correction, the calculated maximum deflection at mid-span is 27.9 mm, with an error of only 1.4% compared to the measured value. Validation under multiple different working conditions shows that this method can control the overall error of bearing capacity assessment within 3% to 5%. This indicates that the CNN-PSO hybrid model can effectively solve the problem of data-model mismatch [7].

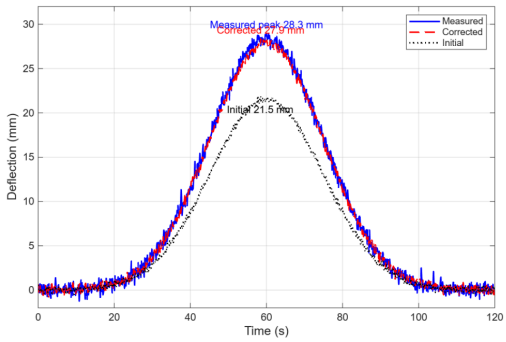

Figure 1. Comparison of mid-span deflection time-history curves

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(Picture credit: Original)

4.3. Analysis of degradation prediction results

The historical monitoring data of the bridge over the past five years (including daily temperature differences, annual temperature differences, and vehicle load spectra) are used to train the LSTM network for trend fitting. After training, the network is used to predict the structural performance evolution over the next three years [8].

The LSTM model successfully captures the nonlinear trend of a slow decrease in the bridge's fundamental frequency over time. Comparing the predicted data of the first year with the actual monitoring data, the prediction error of the fundamental frequency is less than 0.5%. This result verifies the reliability of the model.

It can be clearly seen in figure 2 that under simulated fatigue loading for the next three years (based on a traffic growth model), the LSTM model predicts that the stress range at a critical weld of the main girder will exceed the fatigue allowable stress (120 MPa) for that detail around the 2.5-year mark. The prediction results show that the fatigue damage accumulation rate at this location will increase exponentially in the third year [9].

Based on this result, the system issues a level-2 warning. The warning reminds the maintenance department to carry out detailed inspection or preventive reinforcement at that location by the end of the second year. In this way, the potential risk of fatigue cracking is avoided [10].

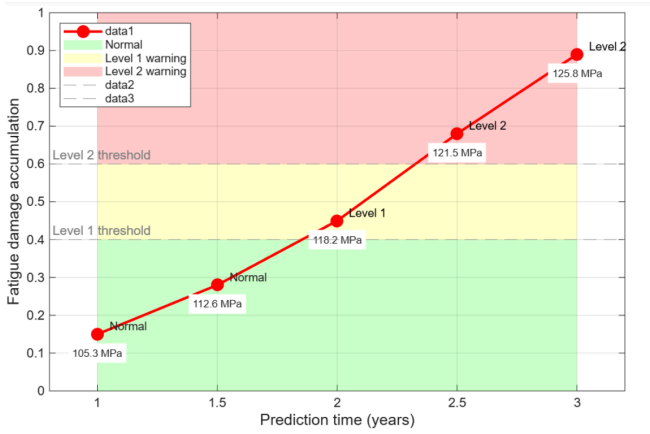

Figure 2. Fatigue damage accumulation prediction trend

(Picture credit: Original)

4.4. Discussion of results

Experimental verification shows that the digital twin–based bridge bearing capacity evaluation method performs well in practical engineering applications. The hybrid CNN-PSO updating method effectively boosts the consistency between the analytical model and actual measured data, and controls the evaluation error within the range acceptable for engineering practice. The LSTM prediction model can precisely capture the slow degradation process of structural performance, offering dependable support for bridge maintenance decision-making. The results also show that digital twin technology has wide application prospects in the field of bridge health monitoring. It helps change the management mode from passive repair after structural damage to active prevention

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ahead of time, and significantly upgrades the intelligence level of bridge operation and maintenance management.

5. Conclusion

This study focuses on performance evaluation and degradation prediction for in-service bridges, and presents a complete digital twin–based technical framework. Using UAV oblique photography and BIM technology, a high-precision bridge geometric model is established and accurately aligned with the real structure, providing a solid foundation for mechanical analysis. The CNN-PSO hybrid model enables dynamic updating of finite element parameters and controls bearing capacity evaluation error within 5%, effectively resolving the data-model mismatch in traditional approaches. The LSTM network further predicts stiffness degradation trends from historical monitoring data and supports early warnings for preventive maintenance.

Although the proposed method performs well in the case of Xinghai Bay Cross-Sea Bridge, it still has certain limitations. The accuracy of model updating relies heavily on sensor coverage and data quality, leading to relatively low reliability in areas with sparse sensors. Meanwhile, the LSTM prediction model is mainly based on historical data and needs better adaptability to sudden events such as overloaded vehicles and earthquakes.

Further research can be carried out in several directions. First, transfer learning and similar methods can be adopted to improve the generalization ability of digital twin models among different bridge types. Second, deep integration of digital twinning with real-time traffic and meteorological data can be realized to establish a more dynamic load field model. Third, lightweight models and edge computing techniques can be studied to reduce computational costs, so as to promote the large-scale application of digital twins in bridge operation and maintenance management.

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