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Digital Twin–Driven Predictive Maintenance System for Bridges

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Abstract. Traditional bridge upkeep is carried out according to time-dependent examinations, yet it has its limitations. It is subjective, expensive, and incapable of predicting an imminent breakdown. This kind of reactive approach, with reliance on manual inspections and scheduled interventions, takes up many man-hours and money for the sake of avoiding destruction without any timely warning. Digital twin technology is the link between the physical and the digital world; it creates a dynamic two-way interaction between the actual bridge and its digital model. This is a symbiosis where the physical being imparts the virtual model with timely data, whereas the virtual entity offers simulations, analytics, and forecasts back to the actual world. As intelligent operation and maintenance systems are being made whole state aware, diagnosing any kind of damage automatically, predicting performance with the latest data and delivering a clear decision to be taken This change is important for modern infrastructure, because moving the ideas from fixing the problem after things go wrong to predicting issues and then prescribing solutions can lead to systems that keep working, live longer, and most importantly make sure that it is safe to get where we need to go using these transportation networks we rely upon.

Keywords: Digital Twin, Bridge, Predictive Maintenance, System Architecture, Data Fusion.

1. Introduction

Bridges are also an important part of transportation. Recently, strengthening the construction of transportation networks and new infrastructure national requirements have raised higher intelligent control and digital management for local infrastructure [1]. Traditional maintenance, depending on manual inspection and post-event repair, spends a lot of manpower and money without timely warning of sudden structural failure. With the increasing difficulty of aging infrastructure, this kind of maintenance can no longer meet the requirements for safety, efficiency, and reliability [2].

Bridge engineering technology progress has developed from a static structure towards Structural Health Monitoring (SHM). Modern SHM systems can now be automatically acquired, but most systems currently focus on the “data dashboards.” They provide data visualization rather than deep analysis or intelligent decisions [3]. The concept of Digital Twin (DT) began in the aerospace industry. It is simple to create a dynamic, real-time, two-way mapping between the physical world object and the virtual world image through its whole life cycle [4]. Compared to the static geometric Building Information Modeling (BIM) models and single-sensor monitoring of SHM, DT realizes

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integration of sensing, modeling, simulation, and decision-making. It gave form to the start to passively respond toward becoming proactively preventive when it comes to bridge upkeep.

2. Theoretical framework of digital twin and predictive maintenance

2.1. Core essence of digital twin

DT is composed of four key elements: a physical thing, a virtual model, a data connection, and interactive services, making a closed loop. A virtual model is generally structured in a hierarchical structure of geometric model, physical model, behavioral model, and rule-based model. The Geometric model can be stated in terms of the geometrical form and configuration of an entity. Physical model: Its behavior in physics. The Behavioral Model reflects the change of the system with respect to time [5].

2.2. Key processes of predictive maintenance

Contrary to periodic maintenance or corrective maintenance, it’s about predicting and preventing failures before they happen. Its typical process entails six principal steps:

(1)Data acquisition

Stressed parts of the bridge, such as main beams, cables, and bearings, are put together with sensor nodes. Strain gauges, accelerometers, and fiber Bragg grating (FBG) sensors are included in these sensor networks. These sensors keep collecting multidimensional info when it comes to structural reactions(stress, vibration) and environmental influences(temp., humidity, wind)

(2) Feature extraction

The system uses some signal processing techniques, such as the Fourier Transform, wavelet analysis, and statistics on raw monitoring data to get some important indices. And frequency, Mode Shape, or Strain Energy all reflect changes to the structure caused by damage.

(3) Condition assessment

Features are then assessed against health baseline models for the bridge features, or historic comparisons, to judge the ongoing health of the bridge and overall levels of damage.

(4) Fault diagnosis

Anomalies identified are then subjected to Finite Element simulations and Machine Learning techniques like Convolutional Neural Network (CNN). The system decides what kind of problem it is, like whether something is cracked or rusty, where the problem is, and how bad it is.

(5) Remaining service life prediction

According to the current damage situation and former loading record data, a composite approach is adopted, which consists of physics-informed models (such as the fatigue accumulation law) and data-informed models (such as the long short-term memory network, LSTM).

This integration will predict how many more cycles will be served by the most important parts in future loading.

(6) Maintenance decision-making

An optimization algorithm is applied considering multiple objectives such as predicted failure time, maintenance cost, traffic impact, etc., to generate the best maintenance timing, scope, and strategy. The ultimate goal is to be able to predict any failures that may occur accurately in order to plan maintenance within the optimal window and therefore get the most out of assets as well as their overall lifecycle [6].

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2.3. Integration of digital twin and predictive maintenance

DT is an enabler for predictive maintenance. It supplies a virtual model that gives a physics-based simulation environment, which enables the development of a prediction algorithm. To get more interpretable predictions, gray-box models those which mix physical mechanisms and recorded info, are commonly chosen. Similar to the Miner's linear fatigue damage can be based upon the real time obtained from the stress spectra measured with its structural monitoring. Compared to fully data-driven blackbox models, it significantly enhances the reliability and physical feasibility of fatigue life prediction [7]. Thus, the deep integration of physics-based and data-driven models is central to the power of digital twins for predictive maintenance.

This paper takes into account existing research and suggests a five-layer intelligent fusion structure for a bridge digital twin predictive maintenance system.

3. Construction of a digital twin–based predictive maintenance system for bridges

3.1. Perception layer

The Perception Layer is the core of the entire system. It gathers information from the physical bridge. Fix all syntax errors. Besides ordinary strain and acceleration sensors, there are new sensing technologies that have been widely adopted. Among these, fiber Bragg grating (FBG) has good anti-electromagnetic interference and strong endurance [8]. UAV Photogrammetry & InSAR Non-contact approach that overcomes spatial limitations for large-scale periodic deformation monitoring. These methods can make up for the shortcomings of traditional point sensors; they have limited coverage and high deployment cost [9].

3.2. Data layer

The data layer deals with the synthesis and forwarding of data from many different and unrelated sources, which is an important matter in digital twin systems. It mainly struggles with key problems like spatiotemporal alignment, noise reduction, and data standardization.

In this case, the Kalman filter is a very popular one, together also other versions based on it, being used frequently on real-time data filtering/estimating the state of dynamic data, greatly improving the overall quality/reliability of analyzing data [10]. At the same time, the transmission of large monitoring data flows can also rely on communication technology, such as 5G and LPWANs, which ensures low latency and long distances.

3.3. Model layer

The model layer is the center of the digital twin. For the geometric model, building a model of information according to reality and combining BIM with reality-based 3D reconstruction to achieve a precise, fine-grained digital Bridge.

Physical modeling uses the numerical method of the Finite Element Method (FEM). The virtual model needs to remain consistent with the physical bridge, which is a huge problem in continuously updating the model. Deterministic approaches (e.g., sensitivity-based updating) as well as probabilistic approaches (e.g., Bayesian updating) have both been well researched. The Bayesian method is especially good at quantifying the uncertainty in model parameters and prediction results, so it fits real-world engineering better [11].

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3.4. Simulation and prediction layer

At this layer, we have the system's primary predictive abilities, which combine several different types of computerization:

(1) Data-driven approaches

Furthermore, learning algorithms, particularly ones like LSTMs, are capable of recognizing temporal patterns and accurately predicting future outcomes based on traffic load and structural changes. These predictions provide valuable foresight for planning bridge maintenance [12]. In addition, by employing a deep-learning-based anomaly detection program that can automatically identify anomalies in massive monitoring data, the foundation for early fault prediction has been created [10].

(2) Physics-driven approaches

The models based on fracture mechanics and fatigue theory, like Paris' law and Miner's rule, make predictions of structural performance from a mechanistic point of view.

(3) Hybrid-driven approaches

Hybrid types are also an optimistic direction for the future. An LSTM might be able to forecast the future load spectrum, and that would then serve as the input for a Miner's rule-based fatigue model to assess the cumulative damage and reach out complementary strengths between data and physics [7, 12]. Recently, PINNs (Physics-informed neural networks) have become a new type of powerful AI modeling tool that directly uses physics equations as neural network loss.

This technique can make a high-fidelity hybrid model, which can be used for a steel bridge's fatigue life prediction [7].

3.5. Application layer

The application layer emphasizes the visualization and decision-making. From other parts of the simulation and predictions layer, such as where damage is and how its performance will be degraded over time, this is layered back into the visualisations via something more visual, like color scales (like going from green to red as healthy to damaged) or dynamic heat-maps and deformation movies.

The system supplies more than just visualization by means of the included DSS: DSS combines prediction results, such as remaining life, with the predictive result of the economic indicator, such as maintenance cost, and with external influences, such as traffic demands. By taking advantage of inherent optimization algorithms for simulation and comparison of numerous strategies for upkeep. Such data-driven suggestions greatly increase the scientific nature as well as the operational effectiveness of bridge maintenance decision-making.

4. Case study: the digital twin project of the Jinkui Bridge in Wuxi

The Jinkui Bridge project in Wuxi is the first and most successful application of the digital twin of large-bridge operation and maintenance in China [14]. We installed about 120 various kinds of sensors (strain gauge, accelerometer, displacement sensor, temperature-humidity sensor) to create a strong perception layer. This network is a multi-dimensional data collection, can collect bridge displacement, bridge vibration, bridge stress, and environmental loads at any time. The data are sent via a 5G network to a cloud-based data center, which forms the data layer and is the ground where a BIM and reality-based 3D reconstruction hybrid high-precision model can be developed in the

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model layer. At the application level, they created a 3D visualization and monitoring platform using WebGL and a game engine framework [13].

The platform displays the bridge's structural health through the colored indicators and animation, which allows the maintenance engineer to notice any possible issues. Through this system, the project has accomplished the initial digitalization of bridge operation and maintenance, making it one of the first projects in China to practically implement digital twin technology for civil infrastructure management.

4.1. Application effectiveness

Carrying out the project has greatly improved the efficiency of bridge operation and maintenance. By means of this kind of system, it was possible to detect potential bearing anomalies ahead of time with abnormal vibration signals, so that some preventative measures could be taken prior to faults, and it turned around bridge management from reactive to preemptive.

4.2. Limitations and challenges

Even though such results were produced, they still show us some problems for furthering our use of digital twins. Firstly, the model layer does not have a dynamic updating function for model parameters after initialization, thus it is hard to keep the model at high precision for a long time. This is the most important problem for getting to achieve high accuracy predictions [11]. Second, for the simulation and prediction layer, hybrid-driven algorithms are not deeply integrated into the system. Its forecasting ability is still restricted, depending largely on simple models and failing to give numerical evaluations of residual service life [7,12]. As well as this, the fusion of multi-source heterogeneous data, like strain, vibration measurements, is still not enough. No strong algorithm yet for joint evaluation of the bridge's structure as a whole, which causes its practicality to be constrained with regard to the damage state of the bridge.

4.3. Challenges revealed and future directions

Jinkui Bridge project practical experience makes it clear what digital twin technology needs to overcome for deeper bridge operation and maintenance integration.

(1) Lack of a dynamic model updating mechanism:

After the parameters of this virtual model were initialized, their values remain mostly unchanged. A key challenge for achieving high-fidelity prediction lies in how to use real-time monitoring data to dynamically calibrate these parameters through algorithms such as Bayesian model updating [11].

(2) Weak predictive capability:

At present, the system mainly focuses on condition monitoring and diagnostics rather than prediction. To realize true predictive maintenance, the simulation and prediction layer needs to be further strengthened by adopting hybrid-driven modeling approaches that combine physical and data-driven methods [7,12].

(3) Limited depth of multi-source data fusion:

There is still a lack of effective algorithms to deeply integrate heterogeneous data of different types, such as strain, vibration, and environmental parameters, to enable a more accurate evaluation of the overall structural damage state. The Jinkui Bridge digital twin project has successfully demonstrated the engineering feasibility of the five-layer architecture and achieved remarkable progress in state awareness and visualization.

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However, it also shows that the current application of digital twin technology in bridge engineering remains primarily at the stages of description and diagnosis [15]. The advancement toward higher levels of prediction and decision optimization will depend on continuous breakthroughs in key enabling technologies, particularly dynamic model updating and hybrid predictive algorithms.

5. Conclusion

This study systematically reviews the bridge predictive maintenance systems with a digital twin.

The research results show that through the establishment of a five-layer architecture - perception, data, model, simulation, and use digital twin technology combined with key technologies such as multi-source sensing, Bayesian model updating, and hybrid-driven prediction, it has the ability to completely change the way bridges operate and maintain, and achieve predictive maintenance.

However, several challenges remain: balancing model fidelity with computational efficiency, achieving deep fusion of multi-source heterogeneous data, and quantifying and interpreting the uncertainty of prediction results. As for future study, I would like to point out the following.

(1) Standardization and Lightweight Implementation:

Low-cost, deployable, and standardized development of digital twins platforms is important for making the technology more widely adopted.

(2) Artificial Intelligence Integration:

An alternative would be to investigate new hybrid algorithms such as PINNs.

At the same time, developing the deep learning-based intelligent anomaly detection and integrating with digital twin systems can effectively make early and accurate fault alarms.

(3) Life-Cycle Data Management:

Ensure smooth data flow and fully tap into the value of data throughout the entire life cycle of the bridge, from planning, construction, and operation to maintenance and decommissioning, so as to improve intelligent asset management. Digital twinning is still in its infancy, yet its deeper application in bridge operation/maintenance shall open up another book in the safety, enduring durability, and intelligent management of infrastructure systems.

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