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Digital Twin Technologies for Structural Health Monitoring

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Abstract. Civil infrastructure such as bridges, buildings, tunnels and dams experiences performance degradation during long-term service because of loading actions, environmental attack and material ageing, and therefore requires continuous structural health monitoring (SHM). Conventional monitoring, however, remains inadequate in terms of data integration, model updating and the linkage with maintenance decisions. This paper adopts a literature review and typical case analysis approach to examine the technical foundations of digital twins (DTs) and their main applications in real-time structural condition monitoring, damage identification and condition assessment, and predictive maintenance and decision support. The analysis indicates that, by connecting physical structures, digital models and real-time monitoring data, DTs can integrate multi-source information from sensor measurements, manual inspections, images, point clouds and environmental and load data. They can also support the dynamic representation of structural condition, anomaly identification and model parameter updating, and provide a basis for safety warning, inspection scheduling and maintenance planning. DTs thereby enhance structural condition monitoring capability and promote the shift of maintenance practice towards condition-based maintenance. At the same time, practical applications remain constrained by data quality, model accuracy, real-time synchronisation and engineering validation, and existing studies are mostly concentrated in the operation and maintenance stage and are based on prototype systems and single case studies. Future efforts are needed in multi-source sensing and data quality control, the integration of physics-based and data-driven methods, standardised data interfaces, lightweight models and whole-life-cycle applications.

Keywords: digital twin, structural health monitoring, civil infrastructure, damage identification, predictive maintenance

1. Introduction

Civil infrastructure such as bridges, buildings, tunnels and dams is continuously subjected to loading from traffic, wind and earthquakes during long-term service, and is simultaneously affected by environmental factors such as temperature variation, moisture attack and material ageing. As a result, structural performance degrades gradually, and structures may eventually develop cracks, excessive deformations or even damage and failure in severe cases. The timely identification of abnormal structural changes is therefore of great importance for ensuring public safety and

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optimising maintenance management. Structural health monitoring (SHM) employs sensors and inspection equipment to continuously acquire information on structural vibration, displacement, strain, cracks, temperature and loading, thereby providing a data basis for judging the safety condition of structures. In practical engineering, however, monitoring data are often scattered across different systems and remain at the stage of collection and display, which makes it difficult to establish an effective connection between monitoring data, structural models and maintenance management decisions. By creating a dynamically corresponding digital model for a physical structure and synchronising the two through data exchange mechanisms, digital twin (DT) technology offers a new technical pathway for linking monitoring data, structural models and management decisions, and has attracted considerable attention in the civil engineering field in recent years.

Existing research on the application of DTs in structural monitoring has focused mainly on the following aspects. With respect to the connection between physical structures and digital models, relevant studies emphasise the use of building information modelling (BIM) as the semantic basis, and associate field monitoring data with structural digital models through the Internet of Things, semantic models and real-time data streams. In the meantime, existing studies have pointed out that traditional BIM and its data formats are mainly intended for information exchange rather than dynamic application scenarios, and that its semantic representation of sensor networks and control systems remains incomplete, making it difficult to directly support dynamic DT applications [1]. With respect to multi-source monitoring data integration, some researchers have reviewed the roles of sensor, laser scanning, image and point cloud data in the construction and updating of DTs, and have considered the efficiency and accuracy of data acquisition and processing as the key issues restricting the development of twin models [2]. With respect to dynamic model updating and damage identification, one study combined a physics-based model with measured data to accomplish model calibration and updating. Data for different damage scenarios were generated in batches with the physics-based model to train a machine learning classifier, achieving rapid identification of the location and severity of damage. The study also quantitatively analysed the effects of sensor number, noise level and parameter uncertainty on identification accuracy [3]. With respect to predictive maintenance, relevant reviews indicate that DTs have extended to the operation and maintenance stage and can be used for condition monitoring, facility management and energy analysis, but analysis, diagnosis and decision-making are mostly based on limited types of data and indicators, and the supporting capability remains insufficient [2, 4]. Overall, different studies have not yet reached a consistent understanding of the components, real-time requirements and validation approaches of DTs; some work directly equates BIM models or monitoring platforms with DTs, and considerable differences also exist in the scope and effectiveness of practical engineering applications [4, 5].

This paper adopts the methods of literature review and typical case analysis to examine the application of DTs in SHM. The paper first introduces the basic concepts and key technologies of DTs and SHM, and explains the composition of DT systems as well as the methods for acquiring and updating structural condition information. It then summarises the application tasks, implementation approaches and practical effects of DTs in three aspects, namely real-time structural condition monitoring, damage identification and condition assessment, and predictive maintenance and decision support, based on published cases. Finally, it discusses the problems of existing research and provides an outlook on future development directions. The main contribution of this paper is to synthesise the implementation approaches and practical effects of DTs across the three application aspects, and to distil the common limitations observed in prototype systems and single

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case studies, thereby providing an engineering-oriented reference for the application of DTs in SHM practice.

2. Technical foundations of digital twins for structural health monitoring

2.1. Basic concepts of digital twins and structural health monitoring

A DT generally consists of a physical structure, a digital model and a data exchange mechanism. The physical structure may be an engineering object such as a bridge, a building, a tunnel or a dam. The digital model can describe the geometric form and component attributes of the structure, and can also simulate its mechanical characteristics and response behaviour. The data exchange mechanism continuously transmits information from field monitoring, environmental loads and operation and maintenance records to the digital model, so that the model can dynamically reflect the operating condition of the actual structure. The core of a DT is not the creation of a three-dimensional visualisation model of the structure, but the real-time representation and analysis of structural condition through the continuous interaction and dynamic updating between monitoring data and the digital model. Sun et al. point out that a DT for civil infrastructure needs to connect physical assets, virtual models, data services and communication networks, and to support applications at different levels such as structural monitoring, diagnosis and prediction [6].

SHM mainly acquires information on vibration, displacement, strain, cracks, temperature and loading through fixed or mobile sensors, and performs continuous or periodic monitoring of the structural operating condition. Such data can reflect the actual response of the structure under dead load, traffic load, wind load, temperature variation and foundation deformation, and can also provide a basis for identifying problems such as material ageing, component damage and connection deterioration. SHM usually includes tasks such as anomaly identification, damage detection, condition assessment and safety warning. Anomaly identification is mainly used to determine whether monitoring data deviate from normal states. Damage detection further analyses the location and severity of potential damage. Condition assessment judges the safety and service performance of the structure by combining structural information. Safety warning is mainly used to identify possible structural risks in a timely manner.

A DT is not the same as a conventional SHM system or a BIM model. Conventional monitoring systems are mainly used to collect, store and display structural condition data. BIM models are mainly used to organise structural geometry information and component attributes. A DT, by contrast, further emphasises the dynamic connection among the physical structure, real-time monitoring data and the digital model. Continuously acquired monitoring data can be used to update the model condition and correct relevant parameters, and to support subsequent structural analysis. Therefore, the role of a DT in SHM is reflected not only in information display, but also in the continuous association of monitoring data, structural models and condition analysis. This association can provide a basis for subsequent damage identification, condition assessment and maintenance decisions.

2.2. Data acquisition and model updating techniques

The data sources required by a DT can be summarised into several categories. Sensor monitoring data reflect the real-time behaviour of a structure under environmental and operational loads by acquiring structural responses such as vibration, displacement, strain, inclination and crack opening. Manual inspection records provide surface-level information such as crack location, corrosion

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degree and leakage, compensating for local deterioration that is difficult for sensors to cover. Image, point cloud or unmanned aerial vehicle photogrammetry data are used to build or correct structural geometric models and to identify surface defects and deformations. Environmental and load data help to explain changes in structural response by measuring temperature, wind speed and traffic or water flow actions. Structural design documents provide material strength, section dimensions, boundary conditions and initial states, which form the basis for establishing digital models. These data carry different types of structural condition information. For example, vibration and displacement can be used to judge changes in overall stiffness, strain and cracks can reflect local stress concentration, and temperature and load data are used to exclude normal fluctuations caused by the environment.

Different types of digital models perform different functions in a DT. A BIM model is suitable for organising three-dimensional geometric information and component attributes, which facilitates the association of monitoring points and inspection records with spatial locations. A finite element model simulates the deformation, internal forces and dynamic characteristics of a structure under loading based on mechanical principles, and can be used for structural response prediction and damage inversion. A data-driven model learns the statistical characteristics of normal and abnormal states from historical monitoring data, and is used for pattern recognition, anomaly detection and trend prediction. In practical applications, one type of model does not usually replace the others; instead, information models, physics-based models and data-driven models are combined according to task requirements. For example, a finite element model can be used to generate response samples under different damage conditions, and a data-driven model can then be used for rapid discrimination of field data.

Data transmission and model updating are the key to ensuring the dynamic nature of a DT. Data collected by field sensors are transmitted to the data platform through wired or wireless networks, and are then linked to the digital model after cleaning, synchronisation and feature extraction. Model updating can be realised through methods such as parameter correction, response matching or data assimilation; when measured responses deviate from model predictions, material parameters, boundary conditions or damage states are adjusted so that model outputs become more consistent with field observations. Measured data can also be used directly to train statistical or machine learning models to update the baseline of normal states. Al-Hijazeen et al. calibrated a DT model using field sensor data from a bridge and performed regression analysis of structural responses with support vector machines to support the monitoring and assessment of bridge structural condition [7].

The reliability of model updating is affected by factors such as data quality and model error. Sensor noise, missing data and transmission delays may introduce deviations into model inputs, and model simplification and parameter uncertainty may also cause discrepancies between predicted results and actual structural condition. In addition, insufficient coverage of monitoring points may limit the identification of local structural changes. Therefore, a DT model needs to carry out data quality control and model validation in parallel during continuous updating to improve the reliability of structural condition analysis.

3. Applications of digital twins in structural health monitoring

3.1. Real-time structural condition monitoring

Real-time structural condition monitoring is a fundamental application of DT technology in SHM. It mainly acquires information on vibration, displacement, strain, cracks and temperature during structural operation through sensors, manual inspection and image acquisition, and associates the

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monitoring data with the corresponding components in the digital model, thereby realising the dynamic representation of structural condition. Compared with conventional monitoring systems, which mainly rely on a single monitoring indicator or fixed thresholds for anomaly judgement, a DT can further combine historical monitoring data, environmental information and structural model analysis results to perform comprehensive analysis of the structural operating condition.

In practical applications, a DT usually needs to synchronise field-collected data with the structural digital model, so that monitoring information can be used not only for recording and display, but also for model updating and condition judgement. As introduced in Section 2.2, the DT-based bridge SHM framework calibrated with field sensor data and support vector machine analysis indicates that a DT can assist in identifying condition changes during bridge operation and support structural anomaly monitoring [7]. Research on intelligent operation and maintenance of railway bridges in China also indicates that a DT can integrate bridge monitoring data, design documents and operation and maintenance information, providing a data basis for structural condition tracking and maintenance management [8].

However, real-time structural condition monitoring is still affected by factors such as sensor reliability, data transmission stability and model synchronisation accuracy. During long-term monitoring, sensor drift, missing data and communication delays may cause deviations between the digital model and the actual structural condition. Therefore, in engineering applications, it is necessary to further strengthen data quality control, monitoring equipment maintenance and dynamic model updating to improve the ability of DT systems to represent structural condition changes.

3.2. Damage identification and condition assessment

Damage identification and condition assessment are further applications built upon structural condition monitoring. Their main task is to determine whether a structure is abnormal by using monitoring data and structural models, and to analyse the location, severity and influence of potential damage on structural performance. By connecting the physical structure, the digital model and monitoring data, a DT can compare actual structural responses with model analysis results, and assist in judging structural condition changes through model updating and data-driven methods.

Compared with conventional approaches that rely on a single monitoring indicator or empirical judgement, a DT can make comprehensive use of multi-source monitoring data and structural information, thereby improving the completeness of condition analysis for complex engineering structures. In specific applications, physics-based models can provide information on structural mechanical responses, while data-driven models can extract characteristics of different states from historical monitoring data; the combination of the two helps to improve anomaly identification capability.

Zhang, Y. Q. conducted DT-based SHM research on hydraulic metal structures such as radial gates [9]. The study combined structural models, real-time monitoring data and data analysis methods, and used methods such as clustering, neural networks and contrastive learning to analyse structural response characteristics under different conditions. The study indicates that a DT can combine structural information in physics-based models with data-driven methods, providing technical support for anomaly identification and condition assessment of complex engineering structures.

It should be noted that damage identification results are still affected by environmental changes, model errors and monitoring data quality. Changes in structural response are not necessarily caused entirely by damage; temperature, humidity and load variations may likewise lead to changes in

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monitoring results. In addition, the number of real damage samples in practical engineering is limited, and the response characteristics corresponding to different damage types differ. Therefore, analysis results obtained from a DT still need to be combined with field inspection and engineering experience for comprehensive judgement, and cannot completely replace professional structural assessment.

3.3. Predictive maintenance and decision support

Predictive maintenance and decision support are further applications of DTs in SHM. By continuously integrating the current condition of a structure, historical monitoring information and model analysis results, a DT can assist in analysing trends in structural performance changes and provide a reference for adjusting inspection intervals, determining maintenance priorities and formulating maintenance plans. Compared with conventional maintenance based on fixed intervals, maintenance carried out based on the actual condition of a structure can make inspection and repair work more targeted.

During long-term service, structural performance is affected by factors such as material ageing, environmental actions and load variations. A DT can track structural condition changes through the continuous accumulation of monitoring data, and assist maintenance personnel in identifying areas requiring attention in combination with model analysis results. The Wanjiazhai Dam safety analysis and early warning system applies DT to the integration and analysis of dam safety monitoring data; by incorporating monitoring information on dam deformation, seepage and stress, the system continuously analyses the dam operating condition and issues safety warnings based on monitoring indicators and model results [10]. The system realises the unified organisation of multi-source monitoring information and provides support for dam condition assessment and safety management.

In addition, the railway bridge operation and maintenance case discussed in Section 3.1 shows that this data integration capability can extend from real-time condition tracking to maintenance planning, providing a consistent data basis for maintenance decisions [8]. These cases illustrate that the main role of DTs in engineering maintenance currently remains data integration, condition analysis and decision support, rather than the complete replacement of manual inspection and engineering judgement.

At present, DTs still face several limitations in predictive maintenance. Structural degradation is affected by multiple factors such as material properties, environmental conditions and long-term loading, and existing models are still unable to describe future structural changes with complete accuracy. At the same time, data loss during long-term operation, equipment ageing and insufficient model updating efficiency can also affect the stability of prediction results. Therefore, it is still necessary to further improve model updating capability, strengthen multi-source data fusion and long-term operational validation, and enhance the application of DTs in whole-life-cycle structural management.

4. Challenges and prospects

Although DT technology provides a new technical means for SHM, its application in practical engineering still faces limitations in terms of data, models and engineering implementation. At present, research on DTs for SHM still lacks a shared technical baseline: the boundary between a DT system and a conventional monitoring platform or three-dimensional visualisation model is often unclear, and reported systems differ widely in architecture, real-time performance and validation depth, which makes it difficult to compare research outcomes or transfer methods between projects.

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In addition, the fusion of multi-source monitoring data remains difficult; traditional data formats such as BIM are mainly intended for information exchange rather than dynamic updating applications, and their semantic association with sensor networks and real-time monitoring systems still needs further improvement.

Data quality and model reliability are also important factors limiting DT applications. In SHM applications, sensor noise, data loss and communication delays may affect the updating of digital models, while model simplification, parameter uncertainty and environmental changes may also cause deviations between analysis results and actual structural conditions. Existing studies have shown that a reduction in the number of sensors, an increase in noise level and higher model parameter uncertainty may all reduce the reliability of damage identification results [2, 3]. Therefore, during DT applications, attention should be paid simultaneously to data quality control, model updating methods and reliability validation of results to improve the accuracy of structural condition analysis.

From the perspective of engineering application, DTs are still at the stage of development from theoretical research to practical deployment. Many current studies focus mainly on the construction of prototype systems and validation with single engineering cases, and the long-term operational performance and large-scale application capability still require further examination. At the same time, DT systems need to be linked with existing information systems in the design, construction and operation and maintenance stages, while insufficient data compatibility and interface standards among different platforms also increase the difficulty of engineering application. In addition, existing research pays more attention to the operation and maintenance stage, and whole-life-cycle applications covering the design, construction and demolition stages are still relatively limited.

In the future, the development of DTs in the field of SHM can be advanced from several aspects. First, multi-source data fusion and data quality control should be strengthened by effectively integrating information from sensor monitoring, manual inspection, images and point clouds to improve the reliability of model input data. Second, physics-based models and data-driven methods should be further integrated so that state identification and predictive analysis capabilities are improved while maintaining the interpretability of structural analysis, and a more complete model evaluation and validation system should be established. Finally, the development of standardised data interfaces and lightweight models should be promoted to enhance data interaction among different systems, reduce engineering deployment costs, and gradually extend the application of DTs to whole-life-cycle structural management.

5. Conclusion

Through literature review and typical case analysis, this paper examines the application of DT technology in SHM. The study indicates that, by connecting physical structures, digital models and real-time monitoring data, DTs enable structural condition information to be continuously updated in the digital space, providing new technical support for structural condition monitoring, anomaly identification and maintenance decisions. In real-time condition monitoring, DTs can fuse multi-source monitoring data and realise the dynamic representation of structural operating condition. In damage identification and condition assessment, DTs can combine physics-based models with data-driven methods to assist in analysing structural condition changes. In maintenance decision-making, DTs can use historical monitoring information and model analysis results to provide a reference for inspection scheduling and maintenance planning. However, insufficient data quality, limited model accuracy, difficulties in real-time synchronisation and inadequate engineering validation remain important factors restricting further application. In the future, multi-source data fusion, dynamic

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model updating, standardised data interfaces and engineering application validation need to be strengthened to promote the further development of DT technology in whole-life-cycle structural management.

Overall, the reviewed cases demonstrate that digital twins can deliver practical value at different stages of structural management, from real-time response tracking on bridges to dam safety early warning and railway operation and maintenance support. Compared with conventional monitoring, the main advantage lies in linking field data with structural models so that condition information can be interpreted rather than merely recorded. Wider engineering adoption, however, will depend on reducing deployment costs, improving data compatibility among platforms and accumulating long-term validation evidence. With continued progress in sensing technology, data standards and hybrid modelling methods, digital twins are expected to become an increasingly routine tool for the safety management of civil infrastructure.

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