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Predictive maintenance and its applications in civil engineering structures: A review

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Abstract: Structural health monitoring and performance prediction are crucial for smart disaster mitigation and intelligent management of structures throughout their lifespan. Recent advancements in predictive maintenance strategies within the industrial manufacturing industry have inspired similar innovations in civil engineering, aiming to improve structural performance evaluation, damage diagnosis, and capacity prediction. This review delves into the framework of predictive maintenance and examines various existing solutions, focusing on critical areas such as data acquisition, condition monitoring, damage prognosis, and maintenance planning. Results from real-world applications of predictive maintenance in civil engineering, covering high-rise structures, deep foundation pits, and other infrastructure, are presented. The challenges of implementing predictive maintenance in civil engineering structures under current technology, such as model interpretability of data-driven methods and standards for predictive maintenance, are explored. Future research prospects within this area are also discussed.

Key words: predictive maintenance; civil engineering; structural health monitoring; machine learning

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Advancements in economies and technologies have significantly enhanced structural theories and construction methods in civil engineering. These advancements have enabled the creation of super tall buildings, long-span bridges, extensive underground projects, and so on. However, during the whole service life cycle, these structures face various factors that could affect their performance. External loads, environmental conditions, material aging, and natural disasters such as earthquakes, floods, and typhoons can cause deformation or damage that exceeds the design specifications, accumulating safety hazards[1]. Therefore, real-time monitoring and diagnosis of structural performance, timely detection of damage, and accurate safety assessments are essential for improving the operational efficiency of engineering structures and ensuring the safety of people's lives and property.

Structural health monitoring (SHM) is becoming increasingly important in civil engineering[2]. SHM uses historical data to evaluate structural performance and ensure safety. It involves data preprocessing and signal analysis to understand the mechanical characteristics and behavior of structures across different dimensions. SHM and data mining methods are crucial for ensuring the safety and sustainability of structures throughout their lifecycle. They are also important components for intelligent disaster prevention and maintenance strategies. Recent research has advanced technologies in signal processing, condition assessment, and damage detection[3–4]. Despite these advancements, nonstandardized policies and complex structural forms pose challenges and opportunities for further research and development[5]. Abnormal vibration events and safety accidents in high-rise buildings have led to social and economic losses, highlighting the need for timely maintenance measures to track and predict structural states and optimize maintenance costs.

1 Maintenance Strategies

During the lifespan of infrastructure, major expenses are incurred during the operation and maintenance phases, comprising approximately 60% of the total cost[6]. Implementing maintenance methods may reduce accident risks, extend the service life of structures, and ensure overall safety.

Maintenance strategies in civil engineering are generally classified into three types[7]: corrective maintenance, preventive maintenance, and predictive maintenance (see Fig. 1). Corrective maintenance, also known as run-to-failure maintenance or reactive maintenance, is activated after a failure occurs. This method is costly and may involve security issues, making it feasible only when the consequences of failure are relatively insignificant. Pre-

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ventive maintenance, referred to as time-based maintenance, involves the periodic displacement of equipment components based on the manufacturer's guidance or experience. Although this method is preventive, rough estimations of component service life can lead to inefficient use and increased system downtime. Predictive maintenance (PdM) monitors and analyzes the current conditions of the equipment to create maintenance plans. PdM aims to prevent failure and optimize efficiency, thereby improving safety, product quality, reliability, availability, and reduction in energy costs[8]. A key component of PdM is early damage detection and the implementation of precautionary measures to prevent failures. Table 1 compares these three maintenance strategies. It shows that PdM balances maintenance and performance costs while increasing availability and reliability[9].

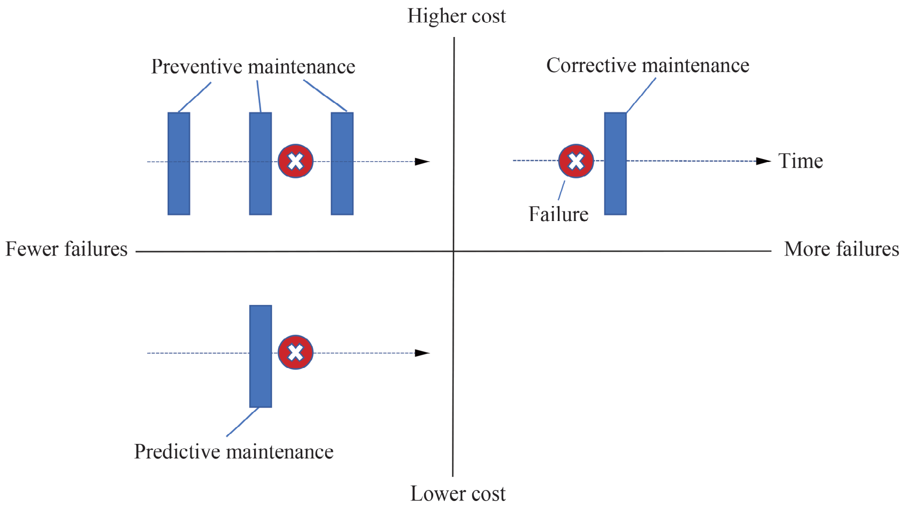

Fig. 1 Three types of maintenance strategies

Table 1 Qualitative comparisons among corrective, preventive, and predictive maintenance strategies

Strategy	Advantages	Disadvantages	Suitable applications
Corrective maintenance	Simple and low preventive cost; maximum utilization	Inflexibility and highly unpredictable failure; potential further threat	Insignificant consequences of failure
Preventive maintenance	Lower repair cost; run for longer	Higher prevent cost; increased planned downtime	Acceptable increased downtime
Predictive maintenance	Efficient and safe; available and reliable; reduction in energy cost	Higher upfront cost; more complex system	Large-scale production mode; process industry; large volume structure

In the following, the framework of the PdM system is first introduced, covering data acquisition and processing, condition assessment, damage prognosis, and maintenance decision making. Existing PdM systems are reviewed. The study delves deeper into the research results and application of PdM technology in civil engineering, especially those focusing on machine learning (ML) approaches. Finally, the discussion addresses PdM values, future research prospects, and the challenges associated with integrating SHM and PdM technologies.

2 Predictive Maintenance

PdM has garnered increased interest across various fields in recent years. The rise of the Internet of Things (IoT) and the development of data-driven algorithms have facilitated the development of data-driven algorithms in industries such as infrastructure management, aerospace fields, energy fabrication and power plants, maritime systems, and industrial production chains. The origins of PdM can be traced back to industrialized countries, where manufacturing enterprises monitored machine performance components to forecast their remaining useful life and conduct maintenance activities before failures occurred[10-12]. Since then, PdM has expanded to other industries with the integration of ML and statistical methods. For example, Li et al.[13] used ML algorithms to improve rail network maintenance. Abbas et al.[14] applied artificial neural networks and support vector machines (SVMs) to predict lost circulation occurrences in oil and gas well drilling. Yuan et al.[7] proposed a system-level life analysis method for proactive tunnel maintenance based on the failure mode and effect analysis approach. Rao et al.[15] proposed a PdM framework for heritage buildings, identifying deterioration through the digitization of building structures. Farahani et al.[16] designed an innovative solution for defect appraisal and health monitoring of railway tunnels using optical devices and computer vision algorithms to obtain tunnel contours and identify defects, subsequently proposing maintenance and repair strategies. Chen et al.[17] discussed system architecture, typical algorithms, and data-driven approaches for the latest research around engineering structures and

PdM. The literature review of PdM systems primarily centers on specific industries, such as tunnel systems[7], power industries[12], and manufacturing industries[18]. This study aims to broaden the scope of PdM research by examining its application in civil engineering, an area that has received less attention in existing literature.

A proper system architecture for PdM should comprise distinct modules that combine to form a cohesive implementation. Fig. 2 shows the typical architecture of PdM, which has the following components: data acquisition, condition monitoring, damage prognosis, and maintenance planning. Emerging technologies have enhanced the potential of identifying precursors and incipient faults in system components, monitoring and predicting damage progressions, and providing decision support or automation for maintenance scheduling[8]. Specifically, IoT could offer a database and a data interaction platform for PdM systems. Various data analysis techniques and advanced hardware can convert large data sets from monitoring into valuable information, providing a professional reference for intelligent maintenance. In addition, state-of-the-art deep learning (DL) methods for damage diagnosis and prognosis enable the abstraction of complex problems with improved accuracy. In the following sections, the PdM modules and the related technologies are presented.

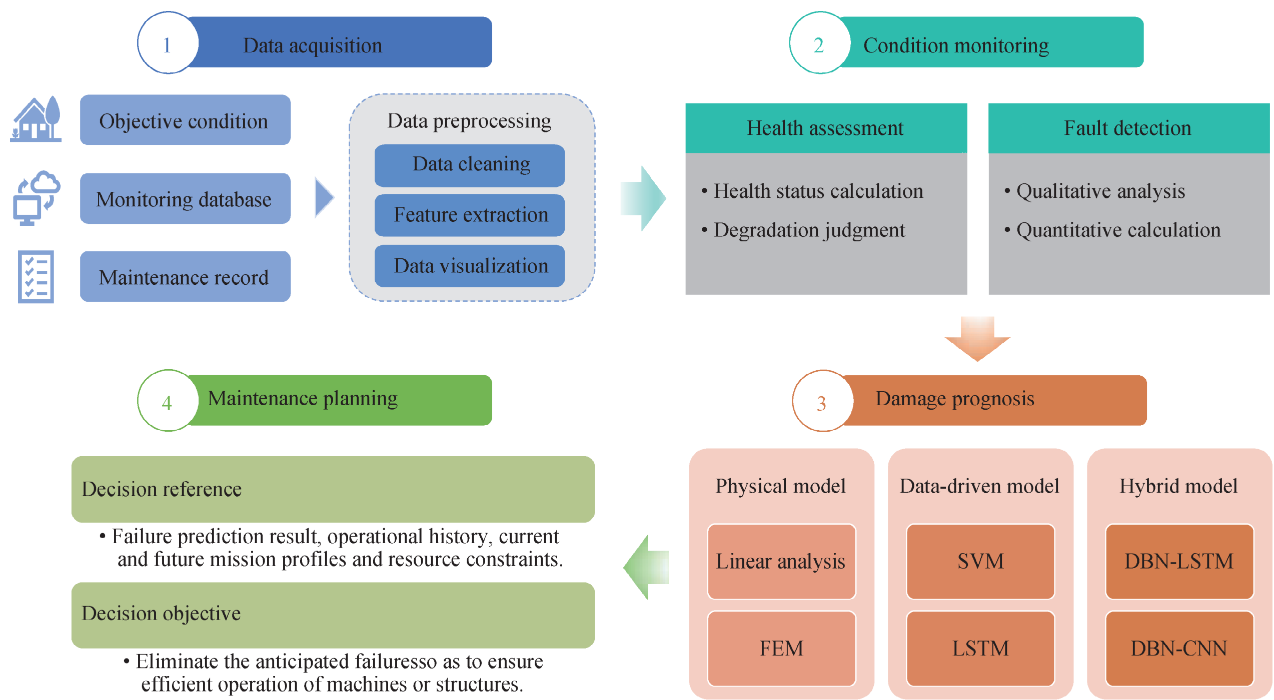

Fig. 2 Typical architecture of a predictive maintenance framework

2.1 Data acquisition

Data acquisition involves collecting data from various sources in real time and storing it in a database. The goal is to collect as much relevant information as possible for PdM, which is essential for assessing the current state of the system and providing the basis for future maintenance schedules.

In civil engineering applications, the data collected falls into three main types: 1) Construction data. This includes information related to project locations and environmental conditions, geographical features, structural types, dimensions of structural members, and building materials. On a microlevel, this also involves collecting data on the chemical composition of structural materials and ecological substances that might affect their properties. 2) Vibration monitoring data. This includes external loadings and the dynamic responses of structures used to infer their condition during service life. 3) Data related to maintenance operations. This includes the safety inspection records and repair history. All this information undergoes a data preprocessing stage, which includes data cleaning, data integration, data transformation, and feature extraction.

Data preprocessing is paramount for delivering meaningful and real information, thereby establishing high-fidelity reliability data-driven models. Since original data often contains noise and may have outliers or missing values, techniques such as wavelet methods, the Kalman filtering method, digital filters, and the Savitzky-Golay filtering algorithm can be adopted to reduce noise[19–20]. Moreover, linear interpolations, spectral analysis, kernel methods, the expectation-maximization algorithm, matrix completion, and matrix factorization are among the approaches to handle missing values[21]. Multiple imputation approaches can also minimize uncertainty through repeated interpolation. Abnormal values caused by external disturbances, human errors, or machine deterioration can be detected using Gaussian-based methods, histogram-based methods, and the DBSCAN algorithm[22].

Non-quantifiable variables (such as construction locations and inspection records) and numeric variables (such as specimen values and structural responses) are available in the database. The order of magnitude of different numerical variables may vary considerably, potentially affecting the training and generalization abilities of the data-driven model. It is, therefore, essential to standardize these variables into a consistent format[23] and normalize them to similar ranges. Techniques such as z-score normalization, min-max scaling, mean normalization, and sigmoid normalization can be adopted. The selection of normalization methods depends on the problem characteristics, PdM tasks, and the requirements of the data-driven models[24].

After preprocessing, features should be extracted to reflect the system state or performance. Data transformation methods include statistical and signal processing techniques. In statistics, methods like dimension reduction (e.g., principal component analysis (PCA)) and partial least squares (PLS)[25], along with nonlinear transformations like locally linear embedding, are used, while in signal processing, time-domain and frequency-domain analysis are performed. Time-domain analysis aims to understand machine operation or the service status of engineering structures by calculating various time-domain statistical characteristics. These include maximal and minimal values, average, variance, standard deviation, root mean square, skewness, kurtosis, and data stationarity. Another approach is time-series analysis, which helps identify linear dependencies, local or global similarity, or short-range or long-range dependencies between two waveforms. Time-domain signals can be transformed into frequency-domain using techniques such as the Fourier transform, the Laplace transform, wavelet transform, and the Hilbert-Huang transform (HHT). These transformations yield results that factorize an orthogonal basis with physical meaning[26].

Data visualization in two-dimensional (2D) or three-dimensional (3D) formats presents processed data and relevant information, aiding in condition prediction and PdM efficiency improvement. Therefore, in addition to databases and analytical algorithms for data mining, designing a graphical user interface for user-data interactions is crucial[27–28]. In interactive data mining, automated scripts can extract the latest analysis data and related information from the database. These scripts, along with specific code programs, enable dynamic data visualization and the exploration of characteristics and correlations.

2.2 Condition monitoring

Condition monitoring gathers data from sensor modules and signal processing modules to assess the current state of system components and detect early failures by analyzing system behavior trends[29]. The condition monitoring module is divided into two parts: health assessment and existing damage diagnosis.

The health assessment aims to determine whether the health of the targeted object has declined[30]. Collected data and analysis results are used to characterize the health status, typically by comparing features against a health evaluation index. This index includes trends in health history, operational status, and maintenance history.

The early failure detection component utilizes historical data analysis or inference engine processing to identify potential issues before they escalate. This component compares real-time data against expected operational limits and triggers a maintenance warning when an anomaly is detected early. The inference engine processes facts and rules to identify patterns and trends that may indicate a potential failure. Once an alarm is triggered, the system automatically records the time stamp and abnormal values in the condition monitoring module for further assessment. Inspectors can then check the relevant components on-site, using their experience, equipment maintenance manuals, or historical data trends to find possible faults and causes.

Damage diagnosis aims to detect, locate, isolate, and repair faults. Methods of damage diagnosis include physical models, expert system methods, and data-driven methods[31]. Physical model-based methods involve techniques such as state estimation and parameter estimation[32–34], requiring accurate mathematical models to describe the structure. Modeling the system helps to understand the mechanism and changes in the process[35]. In practice, the model-based approach detects damage by monitoring the residuals when the signal response reaches a set threshold. Expert system methods rely on qualitative empirical knowledge[36]. This experience-based approach may not consider strict mathematical algorithms for damage detection but instead employs descriptive knowledge of damage symptoms to identify faults in other machines. For example, in the case of a complex engine failure, descriptive knowledge can pinpoint faults in similar machines.

Data-driven approaches include statistical, signal processing, and artificial intelligence, which focus on monitoring data during system operation to diagnose damage without needing to understand the underlying physical mechanisms. They are widely applicable and highly adaptable, especially in areas where exact physical models are difficult to obtain[37]. One such method is PCA, a multivariate statistical analysis method used for diagnosing equipment damage in manufacturing processes. Damage diagnosis based on signal processing can be used in vibration signals using techniques like wavelet transform, HHT, and Kalman filter. Recently, neural networks have gained attention for their effectiveness in damage diagnosis tasks. The parameters of these networks are trained using samples accurately solved in fields that match the current work requirements. Neural networks use implicit representation to encapsulate diverse knowledge pertinent to specific problems within complex networks. This capability allows them to acquire knowledge through parallel associative reasoning[38–39]. This method has been successfully applied in various scenarios, including chemical equipment, nuclear reactors, steam turbines, and rotating machinery, yielding reasonably satisfactory results. It is important to note that the modules of health monitoring, damage diagnosis, and damage prediction share similar analysis methods.

2.3 Damage prognosis

Real-time condition monitoring ensures the security and reliability of maintenance objects in their current state. However, unforeseen failures or performance degradation still pose a risk during the service life of these objects. Therefore, damage prognosis, residual life prediction, or state prediction are crucial for projecting the current health state of the system into the future by estimating future usage profiles[40]. Table 2 summarizes certain prediction models in the literature.

Prognosis can be performed using either a model-based approach, a data-driven approach, or a hybrid of both[54–55] (see Fig. 3). Model-based approaches build a physical relationship between key quantities, working time, and working conditions based on the environment, material characteristics, and failure mechanisms of system components. These methods predict possible failures or the remaining service life of the components using physical laws, making them white-box models. While model-based approaches are often accurate owing to the professional knowledge they incorporate, they require significant time to develop an accurate model. By contrast, data-driven approaches use ML, soft computing, and statistical theories to establish relationships between historical data and target outputs. These black-box models leverage extensive monitoring data and analysis technologies to uncover inherent connections among data points. The versatility of data-driven approaches makes them popular and widely adopted.

With the development of big data, data-driven PdM has become increasingly attractive. To extract useful knowledge and make appropriate decisions, ML techniques such as random forest, K-nearest neighbors, and support vector machines (SVMs) can be applied. Compared to traditional statistical methods, these ML approaches can learn nonlinear features hidden in time-series data[56–57].

Table 2 Literature review of prediction models

Approach	Technology	Target	Application	Year	Reference
Model-based approaches	Physics-based modeling	Cracks	Physics-based modeling of fatigue crack growth	1963	Paris et al. [41]
	Linear regression, kriging technique	Hydroelectric units	Vibration prediction and PdM	2000	Lucifredi et al. [42]
	Particle filtering	Crack and batteries	Prediction of remaining useful life	2013	An et al. [43]
	Physical mathematical model	Building automation systems	Quantitative degradation prediction	2017	Cauchi et al. [44]
Data-driven approaches	AE, XGBoost and SHAP method	Industrial equipment	Prognosis and prediction of remaining useful life	2023	Hoffmann et al. [45]
	MLP and SVM	External gear pumps	Damage prognosis	2023	Lakshmanan et al. [46]
	DBN-FNN	Rotating components	Prediction of remaining useful life	2018	Deutsch et al. [47]
	HHT, SVM and SVR	Bearings	Prognosis and remaining useful life prediction	2015	Soualhi et al. [26]
	MLP, LSTM and CSM-LSTM	Diesel engines	Prognosis and system condition prediction	2023	Calvo-Bascones et al. [48]
	QRF with Bayesian optimization	Bridges	Prediction of typhoon-induced response	2021	Zhang et al. [49]
Hybrid approaches	Particle filter and SVR	Lithium-ion batteries	Prediction of remaining useful life	2016	Liao et al. [50]
	PI-TCN	Bearings	Prediction of remaining useful life	2022	Deng et al. [51]
	Kalman filter and OS-ELM	Aircraft engines	Engine degradation prognostics and remaining life prediction	2019	Lu et al. [52]
	GAN and fuzzy logic	Mechanical systems	Prediction of remaining useful life	2023	Nguyen et al. [53]

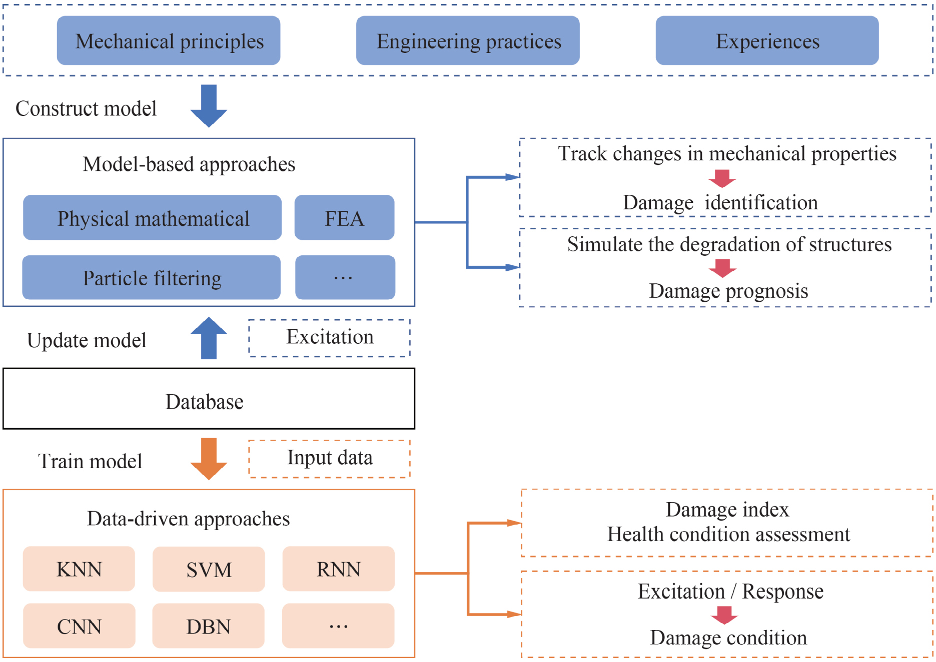

Fig. 3 Qualitative comparisons between model-based and data-driven approaches

Research on deep learning has proliferated in recent years, introducing advanced methods for feature learning, damage classification, and damage prediction within PdM. Deep learning, an extension of ML, excels at extracting complex or abstract features. Techniques such as convolutional neural networks (CNNs), deep belief networks (DBNs), recurrent neural networks, and long short-term memory (LSTM) models are widely applied in PdM. To improve prediction accuracy and robustness, combinations of DL approaches have been proposed, achieving better performance[8]. For instance, some studies have used sparse auto-encoders for representation learning combined with LSTM for anomaly identification[58]. Others have proposed directed acyclic graph networks that combined LSTM and CNN to predict the remaining useful life and many other models[59]. In addition, Li et al. [60] used particle swarm optimization (PSO) and the Markov model to optimize the traditional unbiased gray model, resulting in improved prediction accuracy.

For PdM systems with large-scale or complex components, both model-based and data-driven approaches often fall short of solving all damage diagnosis or prediction problems accurately. Surveys have shown that these approaches may complement each other in PdM systems. Therefore, researchers sometimes employ hybrid approaches to meet different functional requirements in practical applications. The work in Refs. [61 − 62] explores the idea and case studies of using multiple approaches for PdM, including model configuration schemes and application scenarios that address different system requirements.

2.4 Maintenance plans

Maintenance planning, also known as decision making, provides recommendations for maintenance activities and system modifications by considering predicted failure results, operational history, current and future mission profiles, and resource constraints[8]. The purpose is to eliminate anticipated functional failures or mitigate their effects to keep structures or machines operating above minimum acceptable performance thresholds. Frequently, maintenance policy managers and engineers make decisions based on their experiences and educated guesses. However, with the advent of Industry 4.0, there is a trend toward automated and real-time decision-making algorithms. Recent research has focused not only on damage diagnosis and prediction but also on developing decision algorithms for PdM. Bousdekis et al. [18] categorized the decision-making areas into five categories based on the focus and main contribution of each work:

1) Maintenance planning and scheduling. Algorithms in this area recommend appropriate maintenance actions based on company policies, potential impacts, and the risks of candidate actions.

2) Decision making based on reliability and degradation. This area needs algorithms that incorporate degradation rates to minimize long-term costs and schedule mitigating maintenance actions. It considers the trade-off between maintenance costs and structural reliability.

3) Joint optimization. This includes algorithms that optimize maintenance operations while considering other production and supply chain-related objectives.

4) Multi-state and multi-component system optimiza-

tion. This involves algorithms that identify the intermediate stages of the health state, leading to intermediate decision making.

5) Maintenance cost and risk estimation and optimization. This area addresses cost and risk estimation aspects, facilitating decision making for optimal maintenance actions. They may also estimate maintenance costs for different scenarios or identify critical components.

6) Different application scenarios, PdM goals, and predictive models lead to various concerns and maintenance plans during the decision stage. Therefore, maintenance plans should be tailored to the specific needs of applications, considering industry standards, cost optimization objectives, production requirements, actual operational needs, and professional knowledge.

2.5 Existing PdM systems

The development of PdM systems has introduced new technologies, such as cloud computing and IoT, enabling real-time monitoring and predictive analytics for efficient maintenance management. Some PdM systems incorporating these technologies have been developed, such as the open system architecture for condition-based monitoring (OSA-CBM)[63], cloud-enhanced PdM systems[64] and PdM 4.0[29]. OSA-CBM provides a standardized framework for implementing visual PdM systems. It integrates multiple mutually exclusive components and standardizes the inputs and outputs between these components. This feature integrates disparate hardware and software components, which facilitates the efficient management of complex systems. OSA-CBM adds data structures to the ISO 13374 functional modules, defines the interfaces to the functional modules in the ISO 13374 standard, offers auxiliary messaging methods and information, and has built-in meta-data to describe the PdM system. Currently, OSA-CBM has six functional blocks: data acquisition, data manipulation, state detection, health assessment, prognostic assessment, and advisory generation[8].

In addition, cloud-enabled PdM uses cloud technology to store data gathered from sensors, actuators, and other control factors. It performs tasks such as database construction, data cleansing, data integration, feature extraction, and the implementation of prediction algorithms in the cloud. This approach allows the same predictive model to be utilized for various devices, enabling prompt action to prevent asset failures.

PdM 4.0 aims to make industrial maintenance smarter for better production management by integrating system components, IoT, and big data analytics. The PdM 4.0 framework consists of several stages: production simulation, data collection, data storage, preprocessing, data analysis, decision support, and maintenance implementation. Inspired by the needs of Industry 4.0, PdM 4.0 is still in its early stages of development. Each sector should create a customized PdM 4.0 system tailored to its unique features and technological capabilities to offer real-time asset monitoring and predictive alarms.

3 Applications of PdM in the Field of Civil Engineering

The application of PdM in civil engineering is crucial for assessing structural health, predicting damage, and optimizing maintenance management and risk assessment in infrastructure projects. Various PdM frameworks and applications have been developed and demonstrated, including system architectures for housing and utility infrastructures[65], condition-based PdM systems[7] for underground engineering[66], and maintenance decision-making models for road engineering[67]. Existing research in this domain primarily focuses on theoretical frameworks and applicable technologies. This chapter presents various PdM frameworks and applications in civil engineering. The literature review of applications is summarized in Table 3.

In housing and utility infrastructures, Kovalev et al.[65] proposed a PdM architecture that utilizes data mining techniques for damage detection and prediction. For underground engineering, Yuan et al.[7] developed a condition-based PdM system applied to shield tunnels, incorporating a failure mode and effect analysis approach to develop reliability prediction models and estimate the risk of failure and residual useful life. Zhou et al.[66] monitored the deformation of underground tunnels caused by the excavation of deep foundation pits in soft ground, using a coupled model AMSSA-Elman-AdaBoost to predict deformation trends with good accuracy. In road engineering, Li et al.[67] used a GA-improved hybrid neural network (GA-HNN) and a GA-improved backpropagation neural network (GA-BPNN) for maintenance decision making, while Ding et al.[68] used a GA to optimize a back propagation (BP) neural network to predict soft soil subgrade settlement on highways.

In bridge engineering, Xin et al.[69] used an improved variational mode decomposition (VMD) with ARIMA-CKDE to predict deformation. Wang et al.[70] proposed an ML PdM strategy to reduce bridge scour risk. The bridge scour risk ratings derived from ML models were found to be more accurate than those from junior engineers. Despite the fact that the models could only aid in decision making, they also might be a future alternative to on-site inspections. In railway engineering, Allah et al.[71] used multiple models, including decision trees (DTs), RF, and gradient boosted trees (GBTs), to predict maintenance needs, activity types, and the trigger status of railway switches. They used feature importance analysis and the LIME method to interpret results, providing managers with informed decision suggestions. For railroad tracks, Caetano et al.[72] proposed a maintenance

Table 3 References for PdM applications in civil engineering

Reference	Year	Structure	Application	Approach
Kovalev et al. [65]	2018	Housing and utility infrastructures	Real-time condition monitoring, fault and routine event detection, fault prediction and reporting	Machine learning
Yuan et al. [7]	2013	Underground structures	A condition-based PdM system applied to shield tunnels	Weibull and lognormal distributions
Zhou et al. [66]	2024	Underground tunnels	Prediction of the deformation trend of tunnels due to the excavation of deep foundation pits in soft ground	AMSSA-Elman-AdaBoost
Li et al. [67]	2022	Roads	PdM method based on historical road information	GA-HNN and GA-BPNN
Ding et al. [68]	2023	Highways	Prediction of the settlement of soft soil subgrade of highways	GA-BP
Xin et al. [69]	2022	Bridges	Deformation prediction based on structural monitoring data	VMD with ARIMA-CKDE
Wang et al. [70]	2023	Bridges	An ML-based PdM strategy for bridge scour risk reduction	XGBoost, SVM and RF
Allah et al. [71]	2019	Rail transits	A PdM for railroad turnouts	DT, RF and GBT
Caetano et al. [72]	2016	Rail transits	A maintenance methodology for railroad tracks using a multi-objective optimization approach to balance cost and reliability	Tree-based classification
Shan et al. [73]	2024	Large-scale civil structures	A deformation prediction framework validated on a civil infrastructure under construction	STK-EMD-LSTM
Zhou et al. [74]	2024	High-rise buildings	Prediction of vertical deformation based on strain monitoring data	Adaptive unscented Kalman filter
Zhang et al. [75]	2013	Dams	Prediction of the dam deformation	BP and traditional statistical model
Rao et al. [15]	2019	Heritage monuments	Protection of heritage monuments	Predictive analysis method based on statistical technique

methodology attested to a Portuguese railroad network, predicting the geometric degradation of the track using a multi-objective optimization approach that combined cost and reliability for maintenance decisions. PdM also applies to the preservation of historical monuments. Rao et al. [15] proposed integrating the PdM idea with digitization for heritage monuments in India. By using sensor data for predictive analysis, they identified deterioration trends and provided automated maintenance recommendations to prevent potential damage or collapse.

For large-scale civil structures, Shan et al. proposed a novel deformation prediction framework based on a spatiotemporal clustering algorithm combined with an empirical mode decomposition (EMD)-based LSTM network[73]. This framework improved deformation prediction accuracy and efficiency for large-scale structures through a three-level forecasting strategy that includes monitoring point clustering, time-series data decomposition, and deformation prediction. The performance of the proposed framework was validated on real-world civil infrastructure under construction. The results showed that the framework could be effectively adopted for deformation prediction, safety pre-warning, and predictive maintenance systems for various large-scale civil structures with diverse monitoring data. In addition, Zhou et al. [74] predicted the axial deformation of high-rise buildings using an adaptive unscented Kalman filter with on-site strain monitoring data. They introduced anomaly detection to improve system robustness and validated their method on a high-rise building. Zhang et al. [75] built a fusion model based on neural network models with traditional statistical models to achieve accurate predictions of dam deformation. These studies illustrated that PdM is also well generalized to certain special buildings.

4 Challenges and Future Trends

While PdM is an emerging method in civil engineering, several challenging problems still need to be addressed[8]. A review of existing literature reveals that current PdM methods need to consider the effectiveness of big data, model robustness across different engineering structures, and the potential ethical issues arising from the lack of interpretability of models in decision-making processes. In practical engineering applications, PdM methods must handle complex systems with multi-component interactions and consider industry-specific technical standards. Moreover, there is a need for further research on maintenance strategies for such systems. The challenges and development trends of PdM applications in civil engineering are summarized as follows:

1) Data validity. PdM relies on vast amounts of monitoring data. However, data acquisition systems can be costly, and sensor failures may compromise data quality. It is necessary to have accurate, complete, robust, and reliable data. Efficient data preprocessing methods and IoT technology can provide low-cost and high-value big data for PdM. These ensure that monitoring data reflects the real state of buildings during their service life, enabling the solution of practical problems from construction to operation.

2) Model interpretability. Deep neural networks are mostly unexplainable. Owing to the opaque internal operation of DL models, decision errors cannot be fairly and impartially judged according to legal requirements, leading to related engineering ethical problems. Therefore, data visualization and model interpretability techniques should be developed to analyze neural network models.

3) Standards for PdM. In the context of intelligent manufacturing and Industry 4.0, there is a lack of specific standards for civil engineering, and emerging technologies have not been standardized. Therefore, it is necessary to establish standards for PdM systems, designs, and workflows for damage diagnosis and prognosis.

4) PdM for multicomponent systems. As the economy and technologies advance, structural systems are becoming increasingly complex, involving multiple interconnected components. However, most existing PdM approaches focus on damage diagnosis and prognosis for specific components, which may not be sufficient for complex systems. Designing an effective deep learning-based PdM algorithm for multi-component systems and their dependencies remains an open issue.

5) Hybrid network architecture. Different models have different features, strengths, and weaknesses. For example, LSTM can handle long time-series data, while transformers excel at processing large-scale data and deep models. Hybrid network architectures can be explored to improve the robustness and applicability of the model and the entire PdM system. In addition, hybrid models can combine specialized knowledge or engineering experience with DL models to provide a more comprehensive and reliable basis for engineering decisions.

6) Maintenance strategy optimization. Most existing works are devoted to damage diagnosis and prognosis by applying various models. However, minimizing cost targets and downtime while maximizing automation are equally important for designing PdM systems. Therefore, future research should focus on optimizing maintenance strategies.

5 Conclusions

1) The market for PdM is proliferating. The PdM strategy is being embraced across various industries. This approach enables the prediction of potential system damage in advance, the formulation of maintenance plans based on actual production experience, and proactive measures to prevent equipment or structural failure, thereby reducing unplanned downtime and production loss.

2) The recent digital transformation in various industries has further amplified the importance of PdM and its research value, as well as its broad market development prospects. A survey of PdM system architectures, purposes, approaches, and applications in civil engineering is presented. This includes a detailed overview of PdM system architectures, concepts of different modular systems, and the various methods in use.

3) This survey aims to serve as a foundation for researchers and practitioners to gain insights into PdM technologies and protocols. It helps them understand the overall architecture and the roles of the different components that constitute PdM systems. The study also delves into the research and application of PdM in civil engineering, covering areas such as roads, bridges, tunnels, deep foundation pits, industrial buildings, and more. Finally, the study offers some guidance for future research on data-driven solutions and outlines certain challenges and research directions, paving the way for further advancements in the civil engineering field.

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预测性维护及其在土木工程中的应用研究综述

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摘要:结构健康监测和结构性态预测对于结构全生命周期的智能防灾与运维至关重要. 预测性维护策略在工业制造领域的发展促进了相关策略在土木工程领域的探索及应用,例如结构性态评估、损伤诊断和性能预测等. 回顾了预测性维护框架和各种现有解决方案,着重探讨了数据采集、状态检测、损伤预测、维护计划以及成熟的预测性维护系统. 介绍了预测性维护在土木工程领域的前沿成果和工程应用,包括在高层结构、深基坑和其他基础设施中的应用. 讨论了在当前技术条件下土木工程结构实施预测性维护所面临的挑战,如数据驱动方法的模型可解释性、预测性维护标准等,并探讨了在该领域未来的研究前景.

关键词:预测性维护;土木工程;结构健康监测;机器学习

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