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Predicting degraded lifting capacity of aging tower cranes: A digital twin-driven approach

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Highlights

- A digital twin-driven (DTD) framework and model are developed for predicting degraded lifting capacity (LC) of aging tower cranes.
- A DTD model predicted the degraded LC of a scaled-down prototype, achieving a mean-square error (MSE) of 0.2253 and a coefficient of determination (R^2) of 0.9973.
- A DTD model is validated using k-5 cross-validation with a prediction accuracy of 0.97 (R^2).
- Degraded load charts assist operators in placing safe loads and preventing unexpected failures.

Abstract

Aging tower cranes face an elevated risk of failure, primarily due to structural fatigue and deterioration. Surprisingly, the degradation of aging-induced lifting capacity (LC) remains an unexplored domain. In response to this research gap, this paper introduces a digital twin-driven (DTD) framework and model to predict the degraded LC of aging tower cranes. This framework combines theoretical and numerical analysis of fatigue and degradation behavior in tower cranes with real-time vibration data obtained during cyclic load scenarios on the actual cranes. Machine learning (ML) techniques are employed to develop a model that accurately predicts the degraded LC caused by aging. A scaled-down tower crane prototype is adopted as a demonstrative case to illustrate the feasibility and effectiveness of the DTD framework. The DTD model predicts the degraded LC of the prototype with high accuracy, achieving a mean-square error (MSE) of 0.2253 and a coefficient of determination (R^2) of 0.9973. The predicted degraded load charts of the tested tower crane for each decade of usage from 0 to 70 years are also presented to assist crane operators in applying safe loads, preventing unexpected failures and damages, and enhancing workplace monitoring and safety. This study helps monitor the safety conditions of tower cranes that are aging and susceptible to structural fatigue and deterioration, facilitates the prediction of the deterioration of complex machines and systems in the construction industry with real-time data, and highlights the potential of DTD approaches in improving efficiency, safety, and decision-making.

Keywords: Tower crane, Digital twin, Lifting capacity, Safety monitoring, IoT system

1. Introduction

Tower cranes are essential in modern construction projects, facilitating the lifting and moving of hefty modules, equipment, and tools from lifting points to target locations on construction sites [1]. Over prolonged periods of use, however, aging tower cranes may experience structural fatigue, corrosion, and deterioration due to exposure to high-cycle and variable-amplitude loads, harsh working environments, and improper operation and maintenance, leading to degraded lifting capacity (LC) [2–8]. Such degradation can increase the risk of accidents and jeopardize the safety of workers and nearby properties, resulting in severe injuries or fatalities [9]. For instance, in 2022, the tower crane at the "Sau Mau Ping" construction site in Hong Kong collapsed and killed three workers, where the operator set the manufacturer-specified load without considering the deteriorated load and/or capacity [10]. Similar incidents have occurred worldwide, including a crane collapse that killed 18 people in 2016 in Dongguan, China [11], and another crane collapse that killed seven people and injured dozens more in 2008 in New York City in the United States [12]. Thus, there is still a practical need for real-time safety monitoring systems to detect and prevent accidents caused by aging tower cranes with degraded LC.

Various safety monitoring systems have been developed and adopted in the construction industry to address crane safety, including load moment indicators (LMIs) [13–16], anti-two-blocking (ATB) systems [17, 18], and crane cameras [19, 20]. LMIs measure the load on the crane and provide a warning when the load is near or exceeds the crane's maximum LC [13]. Anti-two-block systems prevent the crane from collapsing by limiting its operation when the hook block is too close to the boom tip [18]. Crane cameras monitor the crane's movement and detect unsafe behavior by recording a visual perspective [20]. However, while these systems can improve safety on construction sites, they are generally not designed to address the specific issue of aging tower cranes with degraded LC. For instance, LMIs, ATB systems, and crane cameras do not consider the effects of wear and tear on crane components or the health level of the crane and, thus, fail to predict the internal degradation in LC, which can result in unexpected accidents due to unintentional over-loading. Furthermore, due to the unavailability of historical data on crane operations, the complexity of the deterioration mechanism itself, and the unpredictability of external deterioration-related factors, it remains an open question of how to estimate and update the aging-induced LC degradation.

Many studies have been conducted to tackle the issues of data availability and deterioration mechanism in understanding the degraded LC of tower cranes, which can be categorized into two groups: (1) data-driven methods (DDM) and (2) model-based methods (MBM). DDM uses real-time, historical, and maintenance data [21] to predict deterioration patterns [22]. Several studies have used DDM to predict performance degradation in tower cranes [23]. However, DDM is only effective when data are abundant, and without proper domain knowledge of the deterioration mechanisms, it may be less reliable when applied practically. On the other hand, MBM requires an understanding of failure mechanisms such as cracks, wear, deflection, friction, and stress. One can estimate performance degradation by developing a mathematical model that quantitatively describes the crane’s degradation. However, extensive experiments are required for parameter identification, varying from case to case. Due to the complex nature

of tower cranes, MBM may be less efficient. To overcome the limitations of DDM and MBM, Liu et al. [24] proposed a hybrid approach that combines both methods (DDM-MBM). This approach collects data from multiple sensors since a single sensor cannot capture all the relevant parameters that affect degradation. The use of multiple sensors may increase complexity, but it results in more accurate predictions. Additionally, the mechanical model used in MBM can simulate the structural performance of the tower crane, which increases the interpretability of DDM. Therefore, a hybrid approach that integrates multi-sensor data with an interpretable model could be a possible solution to enable real-time monitoring and prediction of tower cranes' safety conditions considering degraded LC.

As an instance of hybrid DDM-MBM methods, the digital twin-driven (DTD) approach creates a replica of a physical system, aiming to enable real-time data acquisition, response prediction, and human-machine interaction (HMI) [25]. The DTD approach has been widely utilized across various studies for various applications, including product design, manufacturing, planning, maintenance, management, control, traceability, anomaly detection, operational errors, and safety analysis [26–36]. For instance, in a study by Yang et al. [37], a hybrid DTD approach was used to predict the performance degradation in the transmission unit of CNC machines by incorporating damage indices with wear data from Achard wear theory. Similarly, Tran et al. [23] predicted machine degradation by considering both the present conditions of the machine and degradation indices based on a year of data. However, these methods are time-consuming and primarily applicable only to those tools. Despite the extensive use of DT in the degradation field, there is limited research exploring the potential of the DTD approach in predicting the deterioration of complex machines and systems in the construction industry using real-time data. Nevertheless, the mentioned examples from adjacent fields highlight the flexibility and potential of the DTD approach in improving efficiency, safety, and decision-making in various applications.

Aiming to address the real-time safety monitoring and alerting of aging tower cranes, this study develops a DTD framework and model to predict degraded LC after different usage periods. The framework integrates theoretical and numerical analyses of tower crane fatigue and degradation behavior with real-time vibration data obtained during cyclic load scenarios on the physical tower crane. Machine learning (ML) models, including Random Forest (RF) and Support Vector Machine (SVM), are employed for feature selection and LC prediction. Specifically, a scaled-down tower crane prototype is adopted as a demonstrative case to illustrate the feasibility and effectiveness of the DTD framework. The predicted degraded load charts of the prototype for each decade of usage from 0 to 70 years are presented for validation purposes. The proposed DTD framework allows for continuous monitoring of the crane's safety performance considering the degradation in LC with real-time data and numerical model, which is expected to significantly improve safety in construction sites with aging tower cranes.

This paper is structured as follows: Section 2 presents a comprehensive review of the existing research and studies related to the topic; Section 3 presents a DTD framework for monitoring machine deterioration, explicitly focusing on the theoretical background of DTD approaches and numerical analysis of tower crane fatigue accumulation and degradation in LC; and Section 4 outlines the process of developing a DTD model for tower crane degradation

prediction. In Section 5, a case study is conducted using a physical prototype of a tower crane to evaluate the accuracy, efficiency, and applicability of the DTD model. Section 6 discusses the findings of the study. Finally, Section 7 provides concluding remarks, limitations, and directions for future research.

2. Literature review

2.1. Crane safety in construction projects

Construction sites are widely recognized as challenging environments due to the simultaneous and complex nature of multiple hazardous activities. These activities involve the movement of laborers, heavy machinery, and construction materials, thereby amplifying the associated risks [38]. Cranes, being a crucial piece of equipment in construction, not only play a significant role but also pose substantial health and safety concerns for their operators.

Previous research has focused on understanding the causes of injuries and fatalities related to various crane activities, including layout planning, installation/dismantling, erection, and operations. These studies aimed to identify the key factors contributing to crane accidents. For instance, Sulankivi et al. [39] investigated safety issues in crane layout planning, whereas Shin [40] identified the primary factors influencing crane safety during installation and dismantling processes. Chang et al. [41] used 3D simulation and visualization techniques to improve safety during crane erection. Sadeghi et al. [42] developed a framework for ensemble risk analysis to enhance the safety of crane operations. Shapira et al. [43] identified 20 factors associated with crane safety, including project conditions, environmental factors, human factors, and safety management. Finally, Lee et al. [9] found that most crane accidents occur because of human error and crane-related issues. Crane-related problems include structural fatigue, wear and tear, stress, strain, cracks, corrosion, deterioration, and the risk of structural collapse. These issues arise from exposure to cyclic and varying loads, challenging working conditions, and inadequate operation and maintenance practices. As a result, the LC of the cranes decreased over time. Research studies are essential to identify and quantify the degradation of LC caused by the aging of these cranes.

2.2. Analytical approach for crane degradation

Analytical methods use tools, models, mathematical equations, and formulas to address complex problems. In crane assessment, these techniques are applied to evaluate and predict factors such as structural integrity, LC, and overall safety. This approach involves understanding failure mechanisms such as cracks, wear and tear, deflection, friction, and stress, identifying critical components, considering environmental conditions, and analyzing historical data. Relevant information regarding crane usage, environmental factors, and material properties is collected and organized for analysis. Monitoring indicators of early degradation throughout the crane's operational lifespan can help detect potential issues in advance.

Researchers have studied various critical components of the crane to investigate specific failure mechanisms. For instance, Vukelic et al. [44] investigated the failure mechanism of crane gear damage, while Guerra-Fuentes et al. [45] studied the failure analysis of steel wire ropes in overhead crane systems. Das et al. [7] reviewed the failure analysis of hooks, and Wu

et al. [46] developed models for fatigue damage accumulation in critical components exposed to moving loads. Experimental and numerical methods are employed to examine component behavior and identify the root causes of failure. Experimental techniques involve visual inspections, chemical composition analysis, mechanical properties, and hardness tests. Numerical methods, such as finite element analysis (FEA), are utilized to calculate stress/strain and load/deflection, providing insights into the structural performance of crane components. However, it is essential to acknowledge that the analytical method has limitations. It requires a comprehensive understanding of each parameter used in the model and extensive experimental work to comprehend the failure mechanisms of individual components. Therefore, this method may be less effective for complex machines like cranes, as it relies on assumptions and suppositions regarding various parameters.

2.3. Data-driven method for crane degradation

A data-driven method (DDM) analyzes and interprets data to address problems and make informed decisions. It utilizes statistical, machine learning (ML), or artificial intelligence (AI) techniques to collect and scrutinize relevant data related to the degradation of tower cranes. The main goals of this approach are to monitor the operational state and performance of the cranes, predict potential issues or failures, and optimize maintenance and operational strategies. Various types of data are considered, including operational data (e.g., load, usage, and environmental conditions), sensor data (e.g., vibration and temperature), maintenance records, and historical failure data. A thorough analysis of this data is conducted to identify patterns and trends.

For example, Tran et al. [23] conducted a study where they employed a support vector machine (SVM) to predict machine degradation and estimate the remaining useful life (RUL) of machines. They incorporated monitoring and operational data, along with degradation indices, to establish a failure threshold for decision-making. However, it is important to note that the effectiveness of the DDM approach relies on having sufficient data available, and without a solid understanding of the specific domain's deterioration mechanisms, its practical application may be less reliable. Additionally, the data in this particular study was sourced from only one or two sensors installed over the course of a year.

To overcome this issue, Roman et al. [22] introduced a hybrid data-driven fuzzy active disturbance rejection control system for tower cranes. Similarly, Liu et al. [24] utilized hybrid deep neural networks to assess machine performance based on fatigue data. The hybrid approach involves collecting data from multiple sensors, but it can result in complex and computationally intensive modeling due to the increased data volume. This is where the digital twin-driven (DTD) method comes into play, as it allows for real-time data acquisition, prediction of responses, and interaction between humans and machines.

2.4. Digital twin-driven method for crane degradation

A digital twin-driven (DTD) approach utilizes digital twin technology to monitor the operational condition, performance, and potential degradation of a complex physical system, such as tower cranes. A digital twin is a virtual replica of the physical object created through advanced data analytics, simulation, and modeling techniques. Researchers have applied DTD

technology to address various machine performance degradation problems. For instance, Deebak et al. [26] used the DTD method for fault diagnosis in machining tool conditions. In contrast, Zhu et al. [32] used it to control the machining process for thin-walled part manufacturing. Zhang et al. [47] utilized DTD for surface roughness prediction, and Liu et al. [29] employed it for traceability and dynamic control of machine processes. Zhuang et al. [48] utilized DTD to predict wear in the turning process of machines. Jiang et al. [25] focused on the stability analysis of the tower crane hoisting process by examining stress conditions during various hoisting scenarios. Finally, Yang et al. [37] used DTD for performance degradation in the transmission unit of CNC machine tools. However, their approach involved incorporating damage indices with wear data from a specific model, making it time-consuming, complex, and applicable only to that particular tool. Therefore, this study proposes a method for predicting degradation in aging tower cranes based on real-time data, offering a more efficient and versatile approach.

3. Methodology

3.1. A digital twin-driven framework for degradation in machines

The primary goal of this study is to use a DTD approach to predict degradation in machines, such as tower cranes. A DTD framework is formulated based on the mapping between physical and virtual machines, as illustrated in Fig. 1. This framework aims to (1) provide background information, (2) highlight issues, (3) define data requirements, (4) simplify mapping problems between virtual-physical spaces, (5) establish two-way communications between all parts, and (6) make decisions and feedback for improvement. A DTD approach for degradation must have five parts: physical space, virtual space, IoT-based connection, real-time database, and control system [49–51]. Machine degradation is predicted by mapping or fusing the DTD components using DT data.

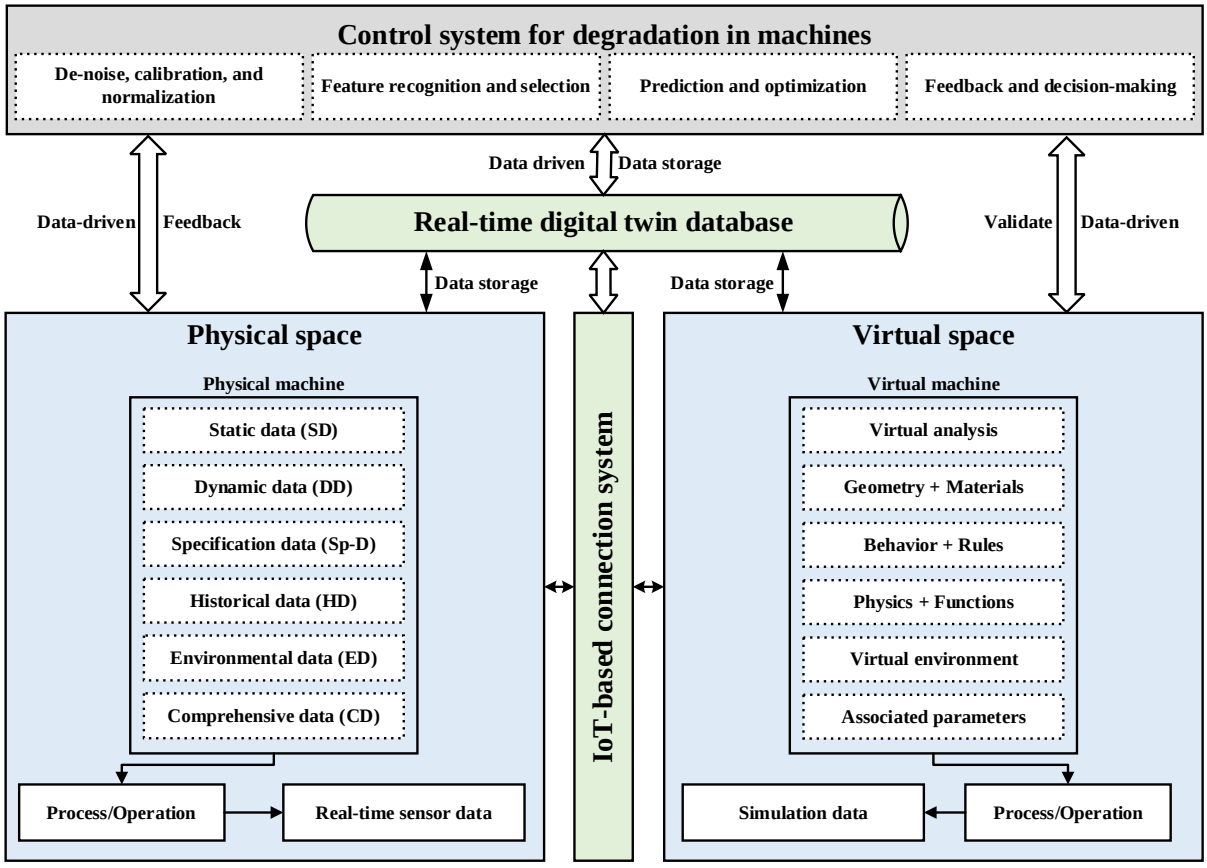


Fig. 1. A digital twin-driven framework for predicting degradation in machines.

3.1.1. Physical space

The physical space module encompasses all the physical activities, operational processes, and work environments contributing to degradation monitoring [25]. To enhance the accuracy and effectiveness of the DTD model, it is crucial to collect data related to element compositions, dynamics, failure mechanisms, and deterioration factors [31]. This requires the installation of sensors and transducers with networking capabilities (such as Wi-Fi or Ethernet) on the physical machine to collect real-time, multi-source, and heterogeneous data. The physical machine may also have a built-in data logging system that records usage information [52]. Section 4.1 will provide a detailed explanation of the various types of additional data required to improve the quality of the DTD model, including static data (SD), specification data (Sp-D), historical data (HD), environmental data (ED), and comprehensive data (CD). Once the necessary data from both the physical and virtual space is collected and a two-way connection is established, decisions can be made, and feedback can be provided for machine monitoring, control, safety, and improvement. The physical space module represents the environment in which the tower crane operates, encompassing the crane structure, components, and relevant sensors for data collection. The significance of this module is highlighted in its role in capturing real-time operational data and physical conditions.

3.1.2. Virtual space

For a DTD approach, it is essential to have a CAD model or virtual representation that accurately captures the machine's features, geometry, materials, behaviors, physics, rules,

functions, and environment [53, 54]. The level of detail (LOD) of the virtual model may vary depending on the specific case and desired data fidelity [47, 55]. With high data fidelity from the physical space, the static virtual body comes to life, reflecting the element composition, dynamics, and real-time status of the physical machine in the virtual environment. Its primary purpose is to provide a realistic description and dynamic simulation of physical entities and processes across multiple dimensions and time scales [25]. The virtual body offers an open interface for data-driven modeling (DDM), optimization, and the ability to predict the current status and remaining useful life (RUL) of the physical machine [52]. In this module, digital twin technology is employed to create a virtual replica of the tower crane. The significance of this module has been clarified, emphasizing its role as a digital representation of the physical crane. This representation allows for the simulation and analysis of the crane's behavior under various operating conditions.

3.1.3. IoT-based connection

In accordance with ISO/OSI communication standards, the communication system for the DTD model can be implemented using either wired or wireless technologies [56]. To establish real-time data transfer and parsing, an IoT-based connection is utilized. This connection serves as a crucial link that facilitates two-way communication between physical and virtual spaces. It ensures that all components of the DTD model are integrated and appropriately mapped to detect and respond to real-time changes in the physical space, as well as to receive feedback from the control system [28, 57]. Additionally, this module ensures secure connection and data transmission between the physical machine and the virtual machine in both directions. Its significance lies in establishing connectivity between the physical and virtual spaces, thereby enabling seamless data flow and real-time synchronization between the physical tower crane and its digital twin.

3.1.4. Real-time digital twin database

Real-time data from the digital twin is utilized to integrate the multi-dimensional and multi-scale virtual simulation model with the physical model and control system. Data serves as the foundational concept of the DTD model, enabling the virtual model to execute operations and make informed decisions. This module is crucial in interpreting, classifying, storing, pre-processing, maintaining, and testing data [26]. This module is responsible for storing and managing the data collected from both the physical crane and its digital twin. The module's significance has been detailed, highlighting its role in storing historical data, enabling comparison and analysis, and supporting predictive maintenance decision-making. The DTD model can effectively access and utilize the collected data for various tasks and processes by leveraging this module.

3.1.5. Control system

The control system within the DTD model plays a vital role in regulating and predicting degradation based on real-time data from the digital twin. It represents the hybrid mode and serves as the most fundamental phase of the DTD model. The control system is responsible for analyzing, visualizing, making decisions, and providing feedback for improvement [47]. It consists of two main components: (1) data pre-processing and (2) a functional module. The

data pre-processing component is primarily responsible for tasks such as online monitoring, de-noising, calibration, normalization, analysis, statistics, and evaluation of raw and real-time data collected from both physical and virtual spaces [31]. This module also includes feature recognition and selection, which is crucial in identifying degradation factors [58]. The functional module incorporates both prediction and visual display capabilities [52]. The predicted results are utilized for decision-making and improvement of the physical machine through feedback. Operators or decision-making teams can directly implement optimization and adjustment plans based on the insights provided. The control system module forms the core of the DTD framework. The crucial role of this module has been clarified by explaining that it integrates data from the physical and virtual spaces, performs real-time monitoring and analysis, and enables decision-making and feedback loops for proactive maintenance and performance optimization.

3.2. Fatigue behavior and deterioration in cranes

Tower cranes are considered to be structures prone to fatigue and are at risk of collapsing during operation [24, 59]. In terms of fatigue behavior, tower cranes are classified as high-cycle and super-high-cycle fatigue structures based on the S-N curve, also known as the fatigue curve or Wohler curve [60]. The fatigue curve represents the relationship between the cyclic stress amplitude and the number of cycles until failure. To analyze fatigue behavior in tower cranes, various approaches can be employed, including stress-life, strain-life, non-destructive, fracture mechanics, and damage mechanics.

The stress-life approach involves plotting stress against the number of cycles until failure [61]. However, this approach requires extensive experimental data, and a single stress-life plot has limitations when it comes to predicting plasticity, deformation, and mean stress. Similarly, the strain-life method entails plotting strain against the number of cycles until failure [62]. This approach requires the stress-strain curve and consideration of plasticity nucleation to determine the transition life between plastic and elastic regions under fatigue loading. Therefore, it is mainly applicable when determining the crack initiation life of the crane structure. Non-destructive techniques can be used to study fatigue by measuring and analyzing inherent properties such as cracks, strength reduction, and stiffness degradation [63]. However, this method necessitates a comprehensive understanding of the relevant parameters and can be challenging to cover all aspects [24]. In fracture mechanics, the focus is on pre-existing flaws and micro-cracks in the structure [64]. The degradation rate is determined using a crack growth law and stress intensity factor as a function of crack depth, shape factor, and stress range. However, our study doesn't consider crane sections with pre-existing defects. Finally, damage mechanics use appropriate assessment models, laws, and patterns to characterize damages, residual stresses, and strain localization [60, 64–66]. Damage mechanics is a suitable approach for addressing tower crane degradation as it encompasses critical factors that directly and indirectly influence crane degradation. For example, micro-plastic strain is often overlooked in low-cycle fatigue problems, but it must be considered in the case of high-cycle or super-high-cycle fatigue damage within the elastic range, as is the case with tower cranes. Macro-plastic strain can result from such scenarios, leading to structural deterioration under long-term operational loading.

While steel structures can have an infinite design life if the stress range is low, tower cranes are prone to fatigue due to the cyclic and varied stress amplitudes experienced by their components during operation. For instance, when a tower crane lifts a heavy load at full stretch and lifting radius, it experiences a higher stress range. Additionally, the loads exerted on the crane are cyclic and have varying amplitudes. As a result, elastic deformation occurs in the crane structure, generating stress and accumulating residual stresses over time. When the residual stresses reach a critical threshold, cracks form, posing a collapse risk for the crane. Therefore, measuring the loads and the associated deflection, deformation, and vibration of the physical tower crane is crucial to predicting degradation accurately.

3.2.1. Fatigue damage accumulation analysis for cranes

There are two main approaches for evaluating fatigue damage: (1) constant amplitude fatigue loading and (2) variable amplitude fatigue loading. In the case of a tower crane, the loads it experiences are stochastic and cyclic, causing fatigue damage accumulation to vary with each loading cycle. As a result, the traditional linear cumulative damage criterion is not applicable in the context of tower cranes [67]. Instead, non-linear and double-linear damage rules are used to account for variable amplitude loads [68].

During the progression of variable amplitude fatigue loading, the tower crane structure undergoes irreversible deformations and accumulates residual stresses. These factors contribute to the initiation and propagation of cracks within the structure. The presence of residual stresses causes cracks to propagate along a particular plane once initiated. These irreversible local deformations and crack propagation significantly impact the overall stability and reliability of the tower crane.

Various parameters can be employed to analyze the damage occurring in the tower crane structure, including total strain, residual stress, stiffness degradation, strength degradation, heat dissipation resulting from micro-cracking, crack propagation, and the speed of sound. In our study, we simulate the mechanical response of the crane structure by considering stress, displacement, and damage index while applying a moving load with variable amplitude.

Existing literature [24, 46, 60, 64–71] indicates that the damage rate in the tower crane is influenced by multiple variables, as expressed in Eq. (1). These variables are used to determine the damage rate of the tower crane structure.

$$dD = f(\sigma_M, \bar{\sigma}, D, \Delta\sigma)dN \tag{1}$$

where dD is the damage rate, σ_M is the maximum stress, $\bar{\sigma}$ is the mean stress, D is the current damage state, $\Delta\sigma$ is the stress spectrum in one cycle, and N is the number of cycles.

3.2.2. Finite-element analysis for degradation index and degradation rate

To assess the accumulation of fatigue damage in the crane structure over a 70-year operational period, we follow the procedure outlined in Fig. 2. While the estimated life expectancy of a tower crane is typically 50-60 years [46, 72], we have chosen to extend the analysis to 70 years in order to enhance the quality and accuracy of the DTD model.

First, we developed a finite element model (FEM) that incorporates the geometric specifications and material properties of the tower crane. This FEM model allows us to analyze the structural performance of the crane under working conditions over a 70-year period. Subsequently, we apply moving loads with variable amplitude to the crane cyclically, considering the material's damage accumulation behavior. This approach allows us to simulate the mechanical response of the crane, including stress, displacement, and damage index.

Fig. 3 provides an example of the damage index contours for a simulated tower crane after 10, 20, 30, 40, 50, 60, and 70 years of operations. A damage index value of zero indicates no damage to the crane, While one suggests complete fatigue-induced damage to the crane model. In this context, the degradation rate (dD) is determined by subtracting the damage index from one, as indicated in Eq. (2).

$$dD = 1 - dI \tag{2}$$

where *dD* denotes the damage rate, and *dI* denotes the damage index, which varies from 0 to 1.

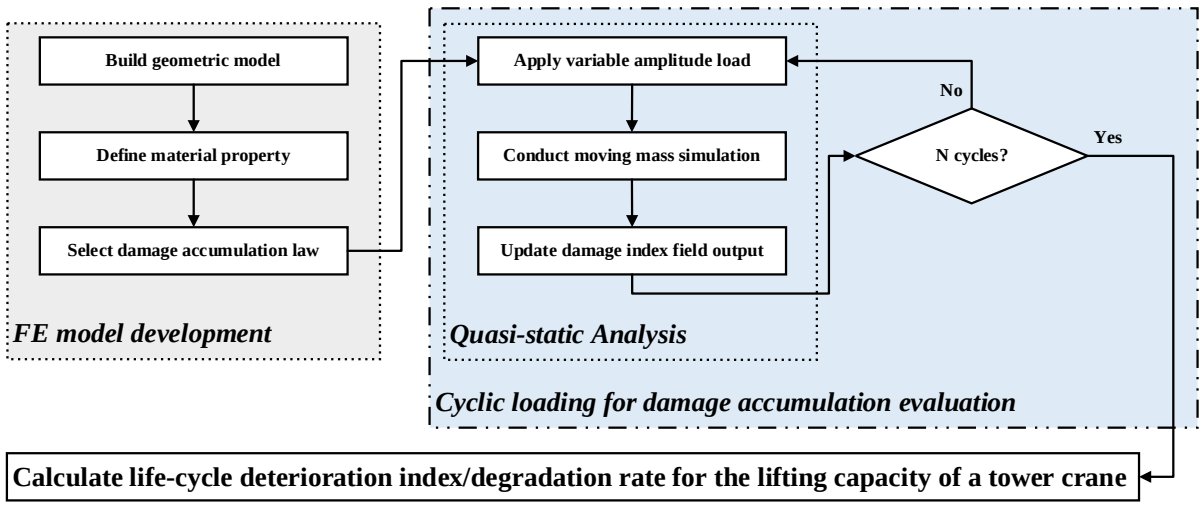


Fig. 2. Numerical procedure for a tower crane's fatigue damage accumulation modeling.

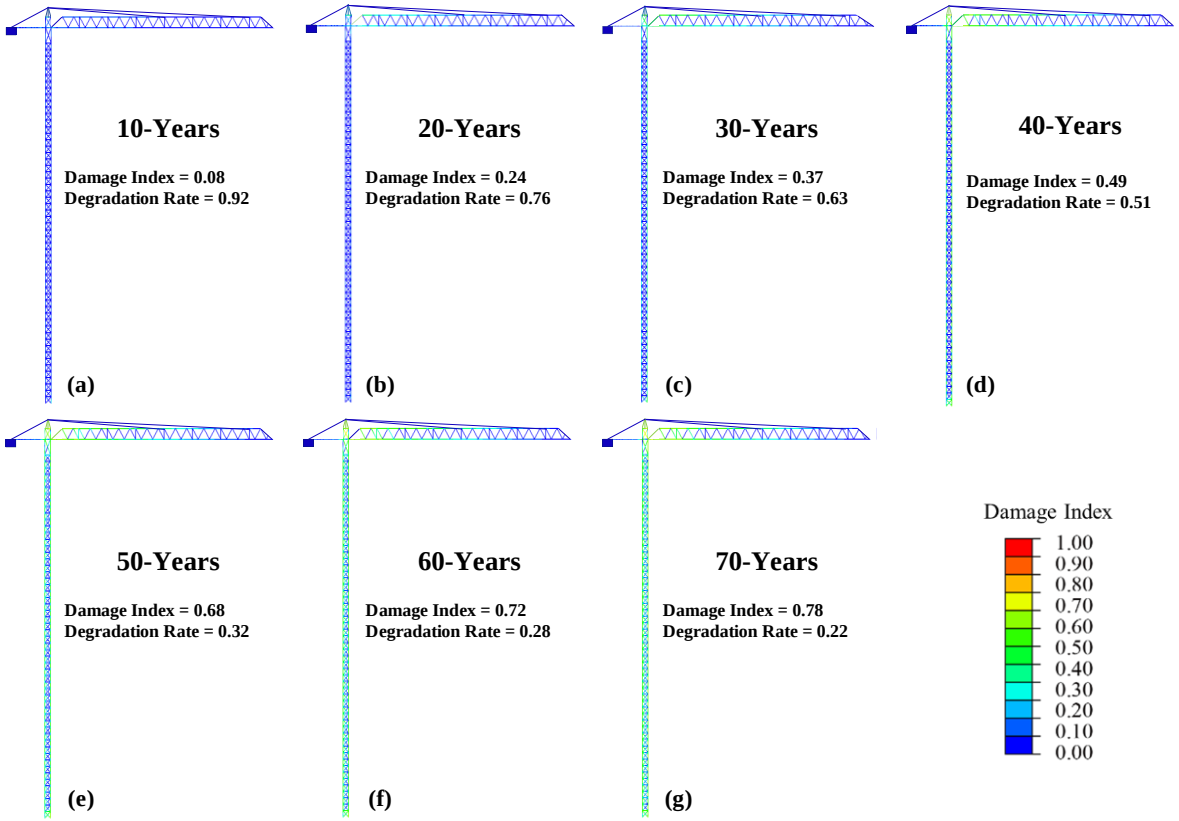


Fig. 3. Fatigue damage accumulation analysis: (a) 10-Years, (b) 20-Years, (c) 30-Years, (d) 40-Years, (e) 50-Years, (f) 60-Years, and (g) 70-Years.

3.3. Data incorporation for degradation

In previous studies, Yang et al. [37] and Tran et al. [23] employed a hybrid model (DDM and MBM) that fused damage indices with real-time sensory data to predict machinery performance degradation. In our proposed DTD model, cumulative residual stress values are integrated as "damage indices" to assess the degradation of tower cranes under cyclic loads over operational periods of 10 to 70 years. These damage indices were derived from virtual simulations of tower crane behavior and seamlessly merged with real-time sensory data, including crane vibrations and load information. The combined dataset is securely stored in a real-time database, such as Firebase, facilitating continuous analysis and monitoring in real-time; stepwise details are included in Section 4.

Following data storage, the DTD model incorporates a pre-processing module that conducts temporal analysis of the sensory data, encompassing time- and frequency-domain techniques to extract relevant features capturing load-induced degradation in tower cranes. These features precisely depict the relationships between load, deflection, and fatigue damage resulting from cyclic loading. As the damage indices cover various aspects of the applied loads and their corresponding deflections, ongoing data analysis uses stress-strain or load-deflection methods, as outlined in Section 5. This involves a comparison of the stress concentrations resulting from the loading cycles to those associated with structural failure. This evaluation allowed the DTD model to train and test a machine learning (ML) model using labeled data. It establishes

associations between sensory measurements (e.g., load magnitude, deflections, stress levels, and cycle counts) and their corresponding damage indicators, indicating repetitive damage.

To ensure the reliability and accuracy of our predictive methodology, rigorous simulations and real-world testing scenarios are conducted to validate its effectiveness. Detailed discussions regarding the reliability and precision of our predictive approach can be found in Sections 4 and 5.

4. A digital twin-driven model for degradation in cranes

This study aims to develop a DTD model for predicting degradation in LC of aging tower cranes, enabling intelligent decision-making, and providing feedback for the lifting operation. As illustrated in Fig. 4, a DTD model consists of five components described in Section 3.1. These components are integrated through the use of DT data. Multi-source, heterogeneous, and real-time data are collected from a scaled-down prototype of a tower crane. This data is then stored in the Firebase real-time database, serving as the foundation for prediction and decision-making within the operational

system. The control system includes pre-processing and functional modules that utilize the collected data for analysis and decision-making. The outcomes and insights generated by the DTD model are fed back to the physical tower crane, improving its performance and monitoring system. Additionally, the control system analyzes and visualizes the collected data, providing operators, decision-makers, and management teams with valuable information for monitoring degradation in tower cranes. In summary, the proposed DTD model facilitates the interaction and fusion of its components to effectively monitor degradation in tower cranes, enabling intelligent decision-making and feedback mechanisms for the lifting operation process.

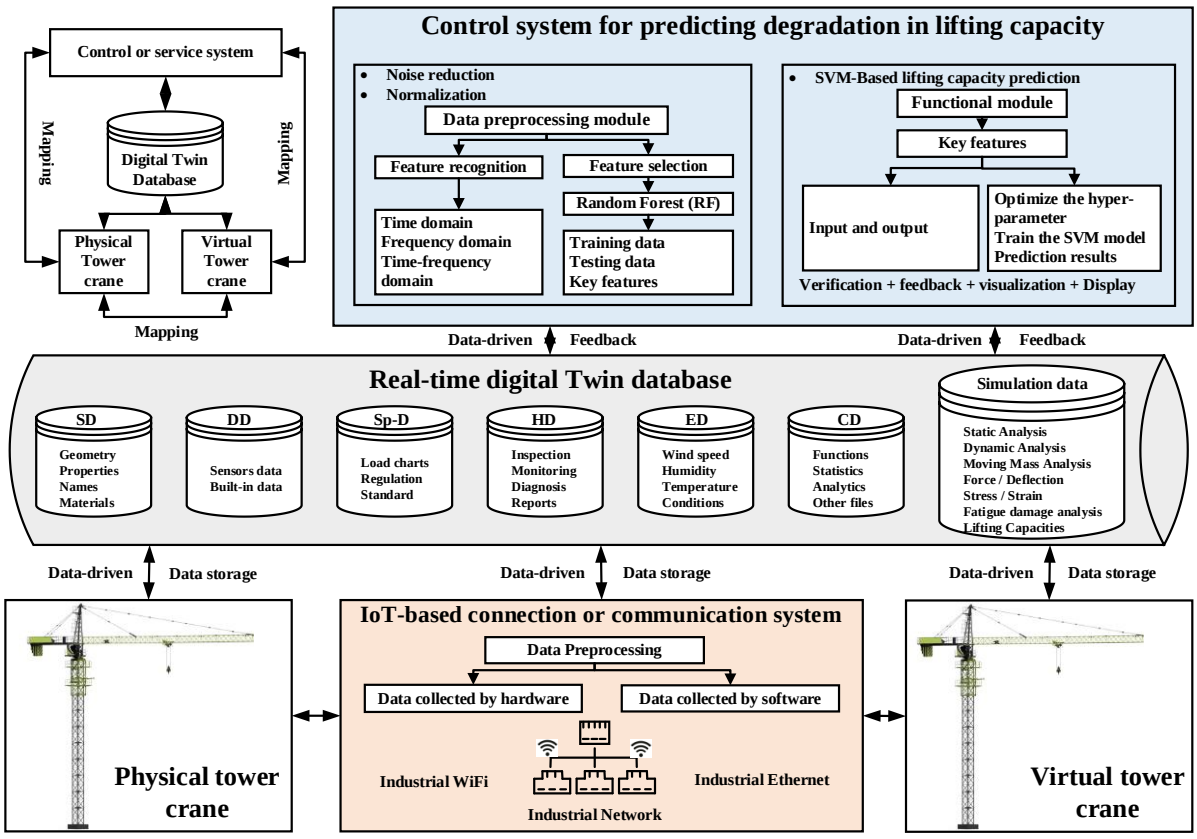


Fig. 4. A digital twin-driven model for predicting degradation in LC of aging tower cranes.

4.1. Physical tower crane

Tower cranes are tall structures commonly used in construction sites to lift heavy objects from the lifting position to target locations. Over time, these cranes experience degradation due to accumulating residual stresses caused by high-cycle and variable amplitude fatigue loads. Researchers, such as Jiang et al. [25], have explored two main areas of study to examine the structural mechanisms of tower cranes: (1) modeling and simulation and (2) scale models.

Modeling and simulation techniques, particularly the finite element method (FEM), have proven to be highly effective in analyzing the internal mechanism, dynamics, and structural behavior of tower cranes [46]. These approaches focus on critical aspects, design optimization, and safety risk performance. On the other hand, the scale model provides another avenue for studying the structural analysis and failure mechanism of tower cranes. Unlike numerical models, physical scale models allow for experimental testing of the crane's operation and control process. This enables easier detection of errors and deviations under various working conditions. He et al. [52] suggested that integrated modeling, simulation, and scale models can improve the structural analysis of tower cranes, predict failure modes, dynamic analysis, and operation processes. This previous research serves as the basis for the proposed DTD model, which employs integrated modeling, simulation, and scale modeling techniques in this study.

The scale model substitutes the large-size tower crane (STL420) structure. The construction of the scale model is based on the principle of similarity, as indicated in Eq. (3). The scale model contains the geometric attributes of all components, detailed in Table 1. The dimensions

of each part of the large-size tower crane are utilized to construct the corresponding scale-down components, as illustrated in Fig. 5. While the large-size tower crane is built using stainless steel, the scale model tower crane is fabricated using plastic materials. However, it is essential to note that the DTD model is developed based on the scale model. Consequently, during the FEM modeling process, the materials used for the scale model are defined as plastic. However, if one intends to apply our approach to a real crane, it is crucial to carefully consider the actual material and geometric properties. These factors play a pivotal role in addressing degradation-related issues effectively.

$$S_g = \frac{L_S}{L_R} = \frac{W_S}{W_R} = \frac{H_S}{H_R} \tag{3}$$

where S_g is the geometric similarity factor, S is the scale model, R is the real model, and L, W, and H are length, width, and height, respectively.

Table 1. Geometric similarity factors.

Structure	Scale size (L, W, H; cm)	Real size (L, W, H; cm)	Scale factor
Mast	(5.5, 5.5, 5.5)	(240, 240, 240)	1/43.6
Jib	L: 60	L: 6000	1/100
Counter jib	L: 22	L: 850	1/38.6
Rope	L: 122	L: 1650	1/13.5
Cross foundation	L*H: 34*19	L*H: 800*800	1/23.5*1/42.1
Load			
R (cm) 6000cm	500(gram)	1.089e+7 (gram)	1/21,772.4

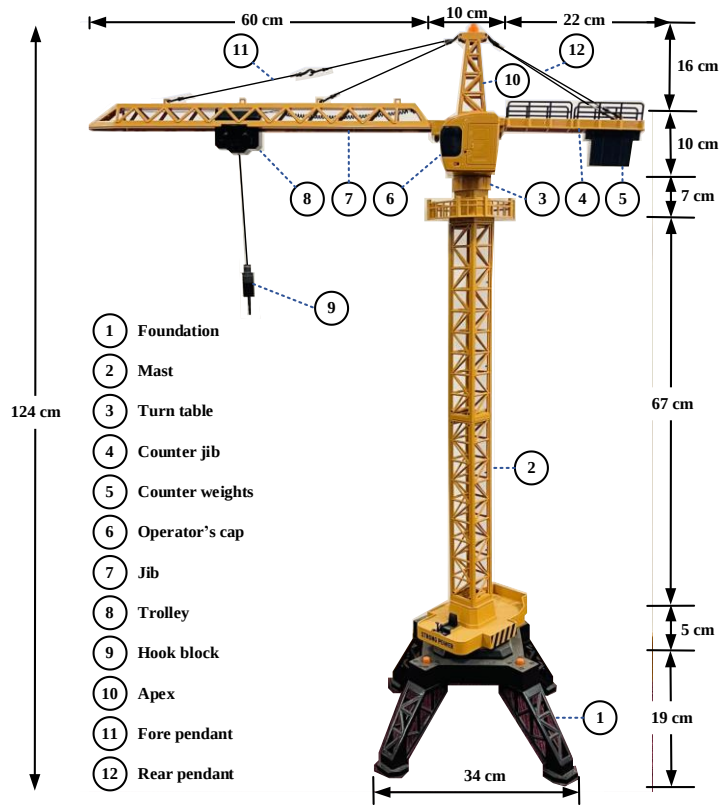


Fig. 5. Scale model of the tower crane and its components and dimensions.

4.1.1. Fundamental data from the physical tower crane

Data is the most essential and fundamental concept in developing a DTD model. In addition to sensors, other data types could be included to enhance the quality of a DTD model, particularly in the degradation scenario. As illustrated in Fig. 6, the tower crane generates multi-source heterogeneous data classified into six categories based on their type and nature: static, dynamic, specification, historical, environmental, and comprehensive data. Static data (SD) is data that does not change with time. Although SD does not directly influence degradation, it can affect quality if altered. In contrast, dynamic data (DD) varies with time. DD provides information about the crane's dynamics, lifting operation, degradation, and real-time operation status. DD is more important than other data types for developing the DTD model. As a result, it requires high accuracy, quality, and timeliness. DD consists of sensors and built-in data. Furthermore, specification data (Sp-D) includes knowledge, standards, and load charts. Historical data (HD) refers to data from inspections, monitoring, and maintenance reports during the service life. Besides this, environmental data (ED) refers to external working conditions, such as temperature, wind, and humidity. Finally, comprehensive data (CD) is additional data other than the previously mentioned data that provides essential and specific information to the DTD model for enhancing prediction and decision-making. In addition, simulation data is required for the DTD model, which we will explain in Section 4.2. Please note that we have developed a DTD model that utilizes real-time sensor data (DD data) and incorporates other data types in specific tasks. This integration enhances the quality and accuracy of assessing the degradation of tower cranes.

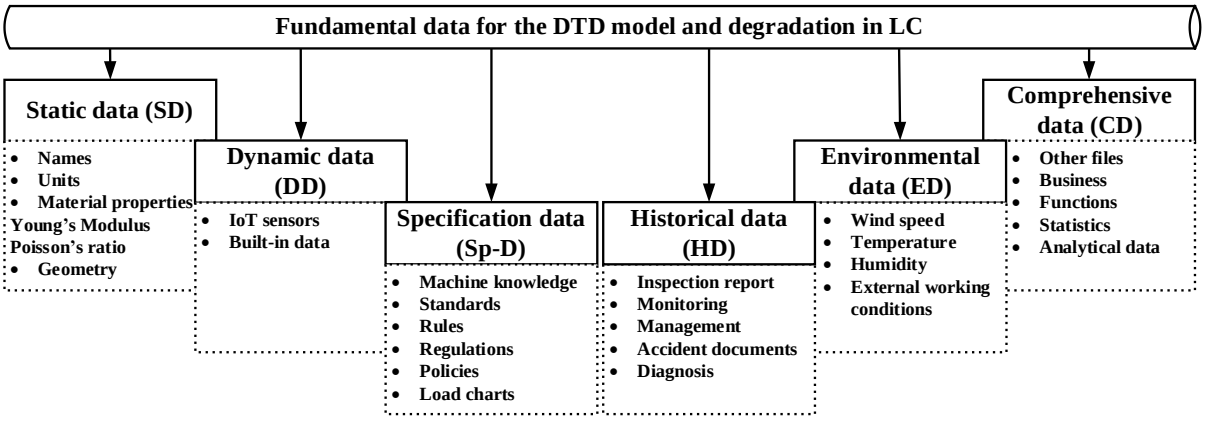


Fig. 6. Fundamental data for the DTD model and degradation.

4.2. Virtual tower crane

The virtual model of the tower crane serves as a simulation platform for analyzing its structure and operations. It accurately replicates the lifting operations of the actual crane, considering factors such as deterioration over time. The ABAQUS software is utilized to create a FEM model of the tower crane, enabling effective numerical simulations to determine the capacity of its structural components in terms of load and deflection. The analysis takes into account the working conditions of a scaled-down model, considering static, dynamic, and moving mass on the crane. All factors relevant to the lifting operations and degradation are incorporated as real-time external data in the virtual model.

The tower crane is connected to its foundation through a baseplate and anchor bolts, which bear the bending moment and restrict movement in four nodal points and six degrees of freedom (DOF). The connection between the mast and jib section is assumed to be rigid, while the junction between the mast, tower cap, and pivoting support is consolidated. The jib and counter jib are hinged to the mast. Finite element analysis (FEA) is performed using various loads, including dead, service, wind, and concentrated loads. This analysis helps determine the LC of the tower crane by examining a force/deflection or stress/strain curve. Additionally, a fatigue damage accumulation analysis is conducted to assess the rate of damage and degradation over a 70-year period. The ABAQUS software stores all relevant information about the lifting operation, including component geometry, mechanical data, operational process, and environmental conditions. Finally, the degradation rate is integrated and used in conjunction with real-time sensor data in the control system of the DTD model to predict degradation in the LC of a tower crane, as explained in Section 3.3.

4.3. IoT-based connection and dataflow

The Internet of Things (IoT) system monitors the real-time status of a physical tower crane. In the DTD model, the IoT plays a crucial role as both a source of real-time data and a source of mechanism for transferring that data. As depicted in Fig. 7, this system is organized into five layers: the object, sensing, communication, data management, and application.

The object layer consists of a scaled-down prototype of the tower crane, which generates real-time data through sensors, as discussed in Section 4.1.1. The sensing layer incorporates

various sensors such as vibration, deformation, deflection, and load cell sensors. These sensors are primarily used for data acquisition and control via different interfaces, such as OPC-UA. The communication layer collects and transfers all types of data using serial port converters and communication modules. It facilitates the seamless flow of data within the IoT system. The data management layer includes a database that stores and integrates essential data translated into different formats. This layer supports functions like perception, knowledge, and algorithms to assist the application layer. Finally, the application layer is the fundamental component of the IoT system. It allows communications between the OPC interface and the server. This layer is for cleaning, association, mining, fusion, and analysis across all subsystems.

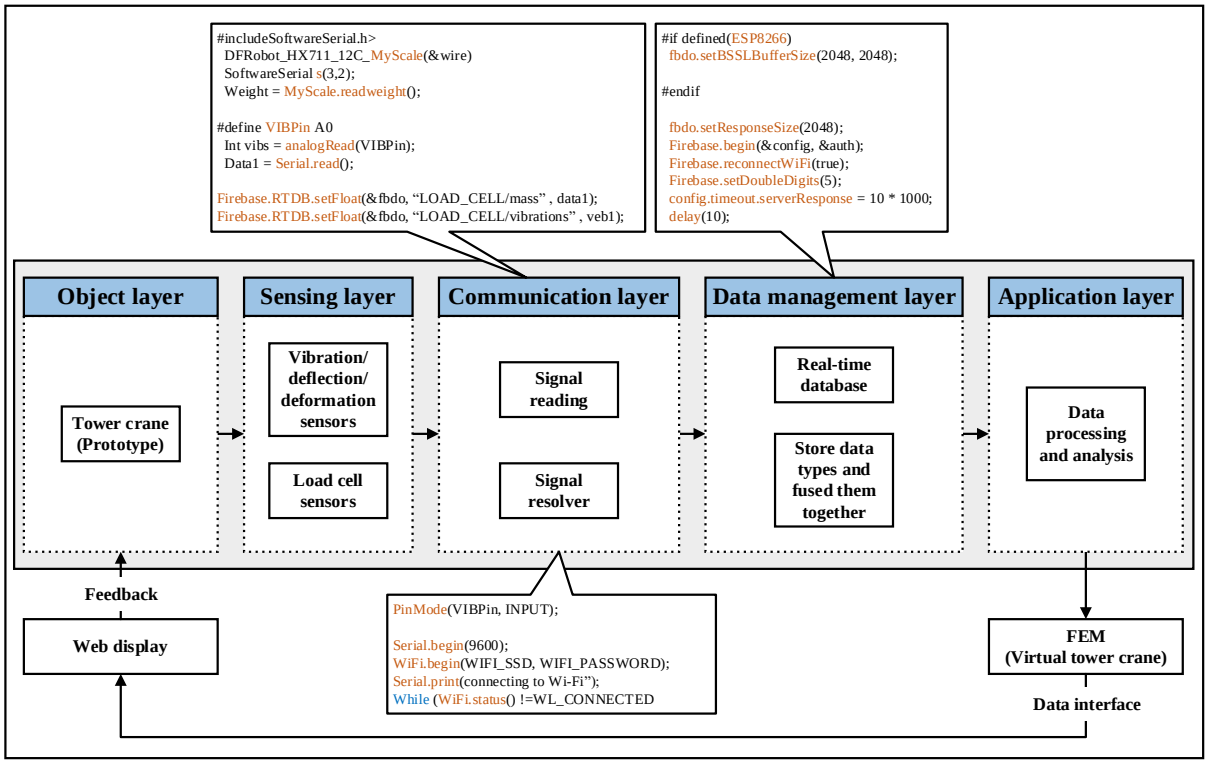


Fig. 7. IoT system and dataflow.

4.4. Real-time digital twin database

To effectively extract critical features related to LC degradation, advanced data conversion technology is necessary. This technology enables the integration and manipulation of sensor data, fundamental data, and simulation data. The diverse nature of LC degradation necessitates using multiple data formats and sources, each with its unique characteristics.

To address these challenges, a Firebase real-time database is employed. This database encompasses all aspects of LC deterioration, providing a comprehensive solution. By leveraging the capabilities of Firebase, the system can handle the complexities arising from various factors influencing LC degradation and the heterogeneous nature of the data involved.

4.5. Control system for predicting degradation

Traditionally, operators and workers are mainly responsible for monitoring and controlling lifting operations. A qualified individual follows the manufacturer's specifications and

directions to ensure a safe lifting operation. The manufacturer's rated loads for a crane are based on ideal conditions. If an individual adheres to the manufacturer's loads for an extended period, the tower crane may be damaged. Therefore, a hybrid and real-time approach is required to illustrate the current status, predict the LC of a tower crane, and present the predicted LC in updated load charts and graphs. The control system is thus designed and comprises (1) pre-processing and (2) functional modules.

The pre-processing module handles data monitoring, analysis, and evaluation for LC prediction. Sensor signals typically contain noise, which can adversely affect the accuracy of LC prediction. Appropriate de-noising methods are commonly employed to mitigate this issue and enhance the precision of the predictions. However, in the context of this study, unique de-noising methods were not utilized as they were not directly relevant to the Firebase database. Instead, we employed two different steps to denoise the raw data. 1) We utilized a communication protocol or interface, such as a Universal Asynchronous Receiver/Transmitter (UART), to transfer data from ESP8266 to an Arduino. This step helped in reducing noise during the data transfer process. 2) We applied the Power Exponential Denoising (PED) method specifically for the load cell. This technique effectively reduced the noise present in the load cell data, further enhancing the accuracy of the predictions. Moreover, data normalization is performed within this module. A feature recognition technique such as time-domain is applied to extract information from the signals. Subsequently, a features selection method is utilized to identify the most relevant features. The dataset is then divided into training and testing datasets for further processing.

In the functional module, important features influencing the LC of the tower crane are selected. Real-time sensor data is utilized by the DTD technique to assess the current condition of the lifting operation. However, real-time data alone cannot predict the degradation rate of LC or how quickly the LC decreases over time. To address this limitation, FEA is conducted to evaluate fatigue damage accumulation and degradation. The degradation rate obtained from FEA is incorporated and manipulated in the database, as described in Section 3. An appropriate machine learning (ML) model is employed to accurately predict degradation in the LC of the tower crane. The high-precision findings are then fed back to the physical tower crane, minimizing unexpected failures and damages while enhancing monitoring capabilities and the overall safety of the lifting operation.

5. Case study

In this study, we utilized a scaled-down prototype of the “STL420” tower crane to evaluate the accuracy, effectiveness, and applicability of the proposed DTD model. Although the prototype has some flaws, none of them hinder our research objectives. For instance, the shape of the foundation/baseplate differs from the actual crane, but the bending moment is restrained to four nodes and six DOFs, mirroring real cranes. Furthermore, the prototype's mast consists of only two sections, whereas the mast of the actual crane has more sections, varying in height. However, this discrepancy does not impact our model since we do not consider critical components or joint failures in the degradation analysis. Finally, although the slewing unit and climbing frame differ in shape, their functions remain identical.

5.1. Physical hardware setup

The scaled-down prototype is equipped with two direct-current (DC) motors that enable horizontal rotation in both clockwise and counter-clockwise directions, trolley movement inward and outward, as well as loading and unloading operations through a remote control. Additionally, as shown in Fig. 8, two sensors, namely a load cell and a piezoelectric sensor, are installed on the prototype to measure the load and deflection. The piezoelectric sensor is positioned at the end of the jib where deflection is higher, while the load cell is mounted beneath the hook. The load cell is connected to the HX711 ADC, Arduino Uno, and NodeMCU ESP8266 Wi-Fi module for data collection and storage. This configuration enables bidirectional communication between the physical and virtual cranes.

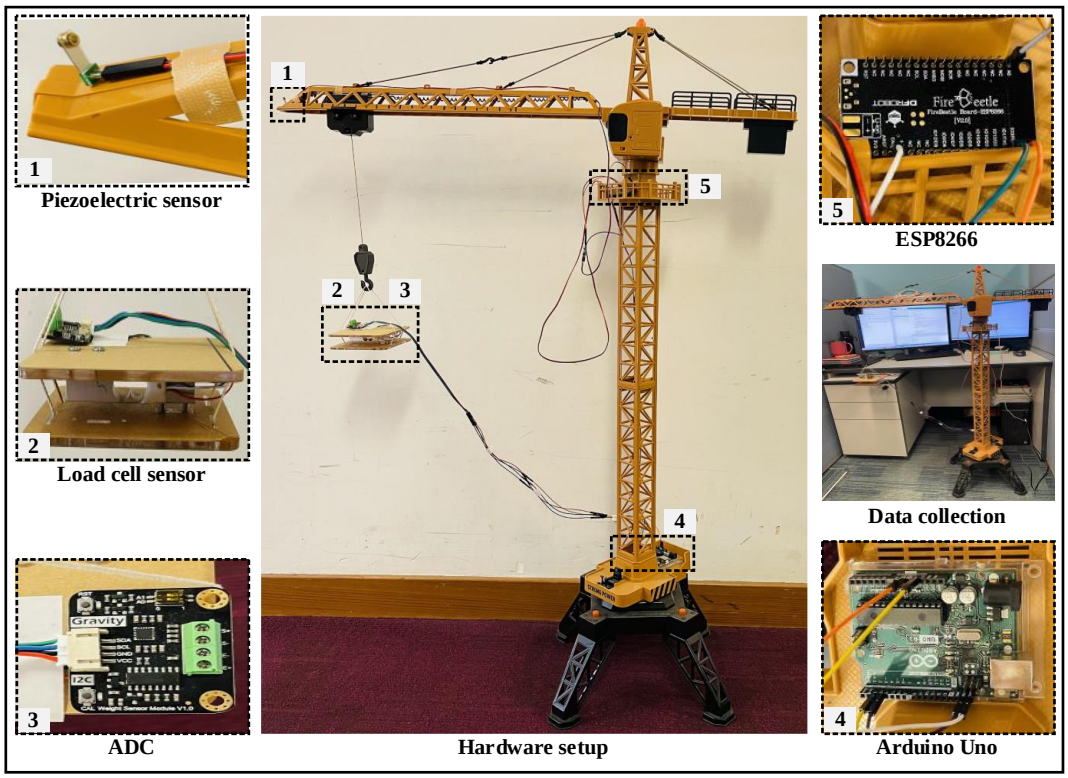


Fig. 8. Physical hardware setup.

5.2. DTD model experimental platform

The main objective of the experimental platform is to conduct lifting operations. A scaled model was constructed to achieve this, and lifting operations were carried out to generate and collect data. In order to measure loads and deflection, a load cell and piezoelectric sensors were installed. Additionally, the actual crane provided three load charts corresponding to counterweights of 12, 18, and 24 tons, along with four jibs of lengths of 30m, 40m, 50m, and 60m attached to the mast. Following the principle of similarity, we utilized a scaled model with a 60-meter jib and 24 tons of counterweights. The load chart for the actual crane is presented in Table 2. Applying the scale factor, the load chart for the scaled-down tower crane is shown in Table 3.

Fig. 9 illustrates the scale model used, which features a jib length of 60 cm and a trolley movement limited to a range of 15 cm to 50 cm. To determine the loads for different lifting radii, we applied scaled-down factors and marked the corresponding radii on the jib using a black marker, as shown in Fig. 8. Each marked lifting radius was then assigned a calculated load. For each point load, three operations were performed to measure load and deflection: (1) loading and unloading, (2) clockwise and counterclockwise rotation, and (3) rotation while loading and unloading. Each point load experiment lasted 10 minutes, during which we completed all three operations. Three tests were conducted for each point load, and the results were averaged. This generated a dataset consisting of 54 experiments conducted at 18 different locations. Simultaneously, the virtual environment simulated the hoisting process. The load values calculated from Table 3 were used to establish the relationship between stress/strain or load/deflection. As discussed in Section 3, residual stresses accumulate when loads are applied cyclically over several years, leading to degradation. Therefore, we calculated seven degradation indices for each load, representing 10, 20, 30, 40, 50, 60, and 70 years. Finally, the degradation rates obtained from the degradation indices were combined and manipulated to real-time sensor data to predict the degradation in LC of the tower crane; a detailed process was explained in Section 3.3.

Table 2. A load chart of the actual tower crane.

Jib (m)	LC_{Max} (t)	Lifting radius (m)														
		20	22	24	26	28	30	32	34	36	38	40	45	50	55	60
60	12	12.00	12.00	12.00	11.84	10.99	10.23	9.56	8.98	8.45	7.99	7.57	6.68	5.97	5.38	4.90
50	18	18.00	18.00	17.26	15.89	14.72	13.70	12.81	12.02	11.33	10.70	10.14	8.95	8.00		
40	24	22.66	20.52	18.74	17.23	15.94	14.73	13.75	12.89	12.12	11.43	10.85				
30	24	23.29	21.09	19.25	17.70	16.36	15.25									

Table 3. A load chart of the scale-down tower crane prototype.

Jib (cm)	LC_{Max} (g)	Lifting radius (cm)														
		20	22	24	26	28	30	32	34	36	38	40	45	50	55	60
60	500	500.0	500.0	500.0	493.3	457.9	426.2	398.3	374.1	352.0	332.9	315.4	278.3	248.7	224.1	204.1
50	750	750.0	750.0	719.1	662.0	613.3	570.8	533.7	500.8	472.0	445.8	422.5	372.9	333.3		
40	1000	944.1	855.0	780.8	717.9	664.1	613.7	572.9	537.0	505.0	476.2	452.0				
30	1000	970.4	878.7	802.0	737.5	681.6	635.4									

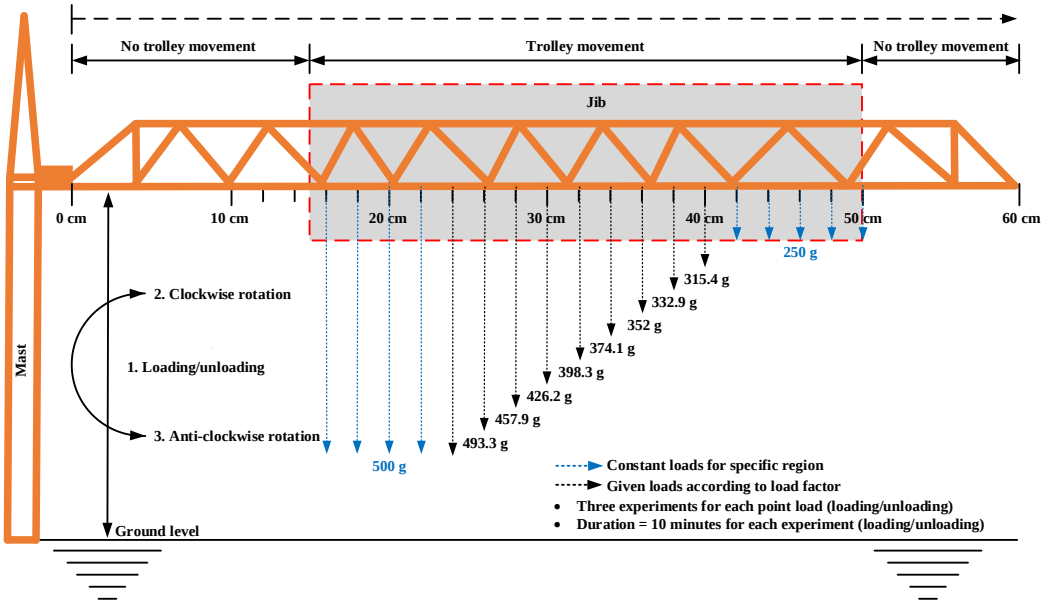


Fig. 9. Experimental platform for the lifting operations.

5.3. Data collection

Fig. 10 illustrates the connection of the load cell and piezoelectric sensors to the analog input pins of an Arduino Uno for data collection and pre-processing. Initially, the raw data is measured as a voltage ranging from 0 to 5 volts at a frequency of 250 hertz. To convert the raw data into integer values between 0 and 1023, a 10-bit HX711 ADC is employed. Subsequently, the load and deformation/deflection data undergo a smoothing process, where an average of 20 measurements is taken for three different weights (100g, 200g, and 300g) to enhance data accuracy and calibrate the measurements. Finally, the smoothed data is multiplied by a predetermined conversion factor to obtain measurements for load (in grams) and deflection/deformation (in millimeters).

Additionally, the data collection module encompasses SD, Sp-D, HD, ED, and CD at various stages of the DTD model. For example, when modeling a virtual tower crane, geometric and material properties are taken into account. In the case of HD, a diagnosis report is examined to assess the precision and accuracy of deterioration, considering the impact of repair and replacement procedures on degradation. Furthermore, environmental conditions such as wind load, temperature, humidity, and others are considered during finite-element (FEA) and fatigue damage accumulation analyses.

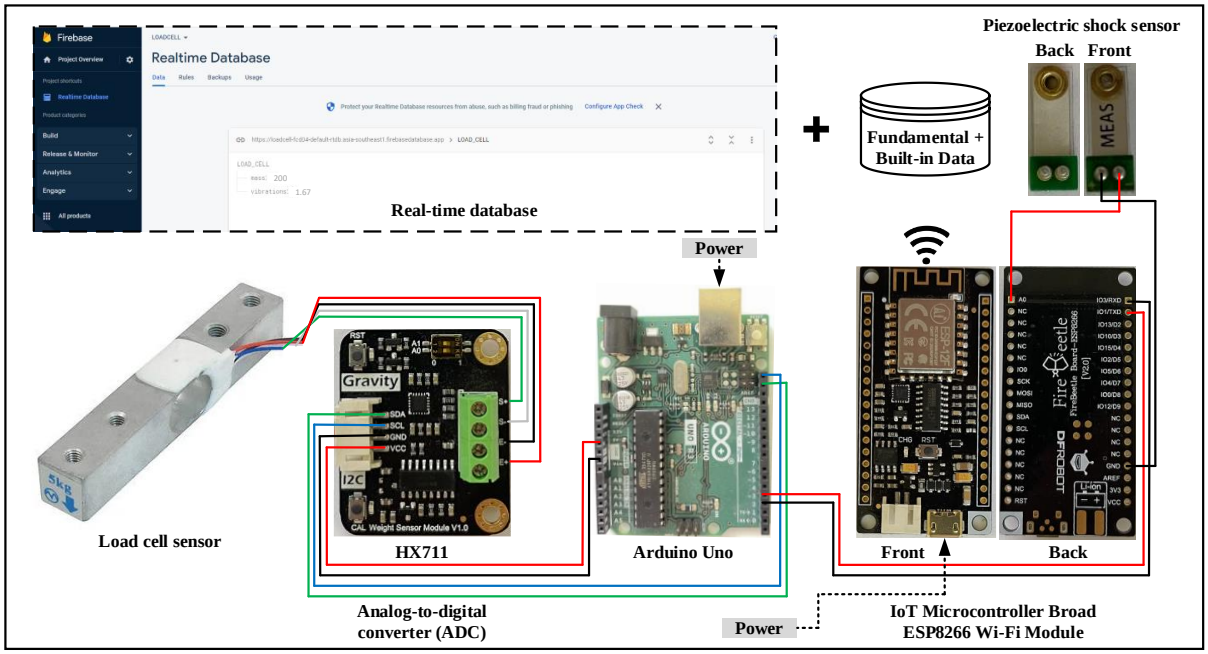


Fig. 10. A circuit diagram or IoT system for data collection.

5.4. Data transmission to the cloud

The Arduino communicates the load and vibration/deflection/deformation data to an ESP8266 module through a serial port. The transmission via serial takes approximately 37 milliseconds, as determined through measurements. To optimize the usage of transmission bandwidth, the average measurements are programmed to be sent every second. This ensures reliable data transmission between the sensors and the cloud gateway. When an average measurement is obtained, the cloud gateway converts the values into JSON format and includes a timestamp.

5.5.FE analysis or simulation environment

The objective of simulation within a DTD model is to replicate a specific process or operation within a virtual environment. ABAQUS software is utilized to construct a finite-element model (FEM) for this purpose. As shown in Fig. 11, a non-linear static analysis is conducted on a crane structure, considering both material and geometric nonlinearity. Variations in boundary conditions, particularly for the boom structure, are also taken into account. The load combination comprises a dead, wind, and lifting load. The equivalent static load is determined by multiplying the static load by a dynamic load coefficient. In the virtual environment, the yield and ultimate strength of the crane material are considered. While the data exhibit a similar pattern, the magnitudes may differ. The crane structure undergoes vibration/deflection when subjected to cyclic loading. Prolonged exposure to such loading and vibration leads to degraded capacity due to the accumulation of residual stresses. We aim to quantify and incorporate the degradation rate into real-time data, thereby reducing the magnitude and aligning the real-time sensor data with the simulation data.

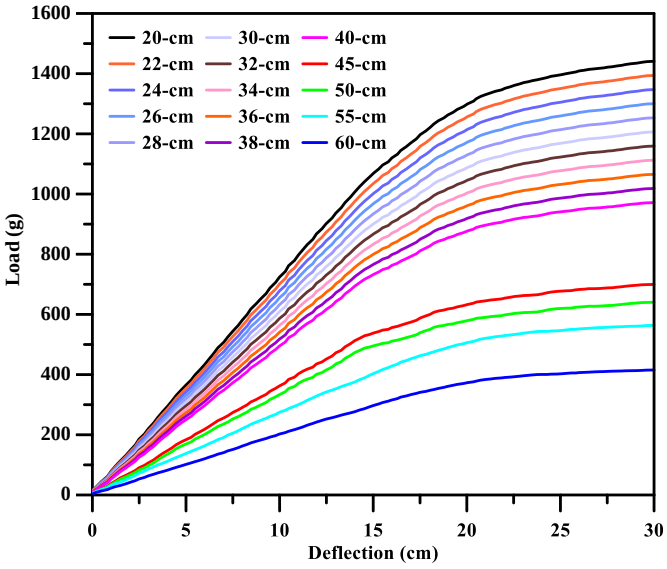


Fig. 11. Non-linear static analysis of the tower crane.

5.6. Control system and synchronization

The ESP8266 devices manage the cloud gateway and the control module, which are connected to the cloud database. Real-time data synchronization is achieved through the use of WebSockets, enabling communication between physical and virtual cranes in both directions. The Firebase real-time database stores sensor data and control codes in this study. The cloud gateway transmits structured data to the real-time database every second. To facilitate backward testing and analysis, each simulated value is stored in the historical database. The JSON objects consist of six layers of nodes, which is advantageous for training machine learning (ML) modules due to variations in sensor data features across operational nodes. Consequently, a machine learning-based classification engine can effectively utilize this historical data.

5.6.1. Historical data hosting and computation engine

While establishing a direct relationship between load, deflection, degradation rate, and LC poses challenges, a machine learning-based classification engine can effectively utilize historical data. The training and testing process relies on data collected during the idle state, ensuring that operation only commences under safe conditions. Initially, the sensory data is pre-processed by grouping values into 10-second intervals. For each sensor, a rolling standard deviation is calculated to generate additional features for ML. The most recent timestamp is used for the aggregated data, and the state with the highest count is considered the congregated state. Delta time is disregarded as it does not contribute to the learning engine. A one-class categorization method based on similarity is implemented, utilizing a support vector machine (SVM) model. The model learns the characteristics of typical scenarios and predicts whether incoming input deviates from these specific occurrences. Finally, the dataset is validated by analyzing the model's accuracy using k-fold cross-validation. To simplify matters, a control system is divided into two modules: pre-processing and functional.

5.6.2. Preprocessing module

The pre-processing module monitors, analyzes, and evaluates real-time data related to the lifting operation. The raw or sensory data contains crucial information that influences the LC. Feature recognition techniques, such as time-domain, are employed to extract the relevant features from the signal. Key features for the LC, including Load (g), deflection (mm), boom length (cm), lifting radius (cm), counterweight (g), and degradation rate, are determined as the primary factors. While considering all parameters that affect degradation and LC is challenging, incorporating optimal parameters can enhance prediction accuracy, as noted by Roysson et al. [73]. The random forest (RF) model is employed to select the features after feature recognition. RF combines the CART tree and random subspace, where a CART tree consists of decision nodes, leaf nodes, and root nodes. Each tree is constructed using the independent random sample approach. The bagging or bootstrap technique creates subsets, and a random subset of feature attributes is chosen based on a specific criterion. RF generally outperforms single decision trees due to the voting-based selection of outcomes from multiple trees. In this study, the essential features are selected using different n-estimator hyperparameters, namely 100, 250, 500, 750, and 1000. The dataset is divided into 70% training and 30% testing sets. The importance values for the Load (g), deflection (mm), boom length (cm), lifting radius (cm), counterweight (g), and degradation rate are 0.37, 0.34, 0.13, 0.14, 0.0, and 0.2, respectively. In this case, the counterweight importance is zero as it remains constant during lifting. Table 4 presents the errors and R^2 values obtained from the RF feature selection process.

Table 4: Errors and R^2 values for the random forest (RF).

Model	Hyperparameter	Trees	Mean absolute error (MAE)	Root mean square error (RMSE)	Mean absolute percentage error (MAPE)	R-square (R^2)
Random forest (RF)	n-estimator	100	0.174	0.232	2.1%	0.997
		250	0.168	0.227	2.1%	0.997
		500	0.166	0.225	2.0%	0.997
		750	0.169	0.226	2.1%	0.997
		1000	0.168	0.225	2.1%	0.977

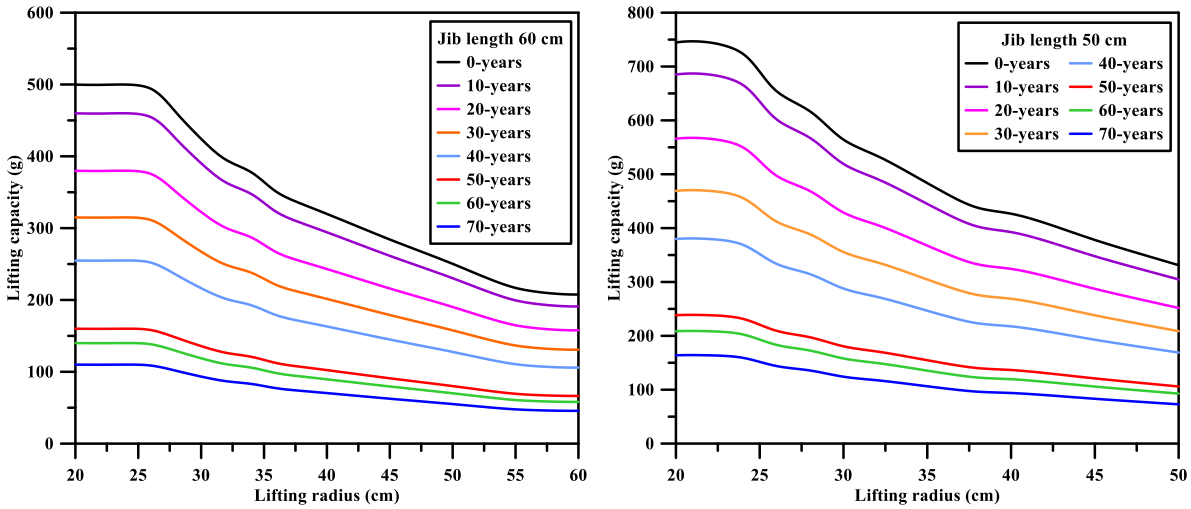
5.6.3. Functional module

Predicting the complex and non-linear problems of LC and its degradation using traditional mathematical models is challenging due to their multi-variable nature. In this regard, machine learning (ML) provides significant advantages for accurate prediction. The SVM model is employed to predict degradation in LC, as it excels in handling high-dimensional data with distinct margins and scattered data points. To ensure the model's accuracy, the authors utilized a 70% dataset for training and reserved 30% for testing. The input variables consist of Load (g), deflection (mm), boom length (cm), lifting radius (cm), counterweight (g), and degradation rate, while the output variable is lifting capacity (g). Evaluation of the model is performed

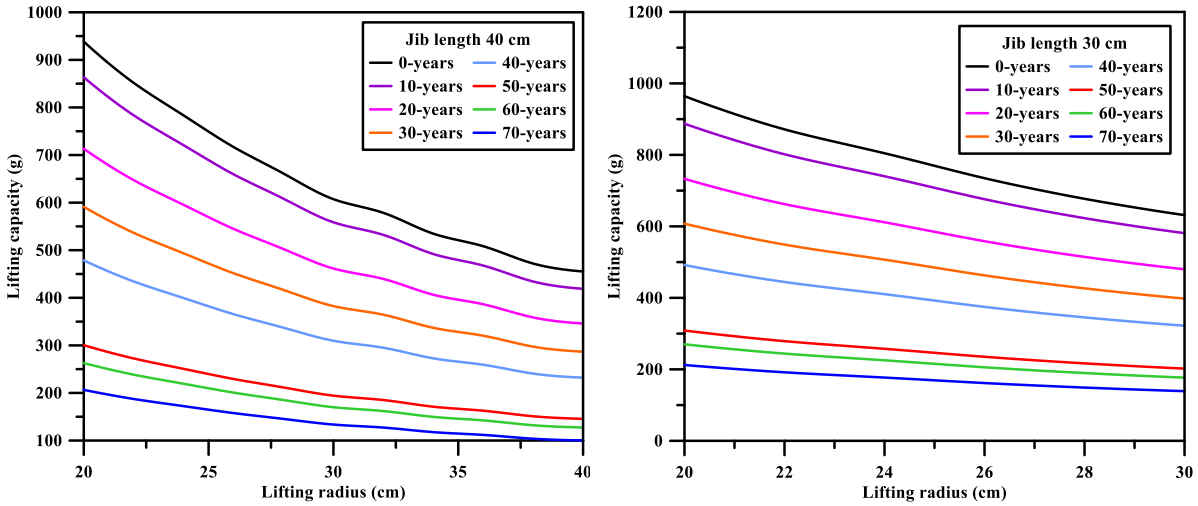
based on two criteria: mean square error (MSE) and coefficient of determination (R^2). MSE measures the average squared difference between the predicted values and the actual values, reflecting the prediction error. On the other hand, R^2 represents the proportion of the variance in the dependent variable (LC) that can be explained by the independent variables (load, deflection, boom length, lifting radius, counterweight, and degradation rate). R^2 values range between 0 and 1, with values closer to 1 indicating a better performance of the prediction model and smaller prediction errors. Smaller MSE values and R^2 values closer to 1 indicate smaller prediction errors and better performance of the prediction model. In this study, the MSE and R^2 values are reported as 0.2253 and 0.9973, respectively. These values demonstrate that the SVM model is a good fit for the data and analysis, as it accurately predicts the outcomes. It is worth noting that high-quality, consistent, and reliable sensor data contribute to achieving high R^2 values.

The evaluation of the DTD model reveals its flexibility and accuracy in predicting degradation in complex machines such as cranes. The degradation rate is integrated into the control system, calculated based on fatigue damage accumulation and FE analysis. Fig. 12 illustrates the predicted degradation in LC for a tower crane, where the predicted results of LC (g) are plotted against the lifting radius (cm) for a boom length of 60cm. The predicted results are scaled for boom lengths of 30cm, 40cm, and 50cm by multiplying them with a scale factor.

Table 5 displays the predicted load charts for a prototype crane, considering 0 years and 70 years of operation. The high-precision findings obtained from the model are fed back to the physical tower cranes. Moreover, Table 6 demonstrates that when the load chart of the prototype is scaled using a scale factor, it matches the load chart of the actual tower crane. By calculating the degradation rate and continuously updating the load chart over the service life of the tower crane, operators, management, or decision-making teams can make informed decisions regarding crane operations and maintenance planning, considering more accurate LC information.



(a) Jib length 60 (cm) (b) Jib length 50 (cm)



(c) Jib length 40 (cm) (d) Jib length 30 (cm)

Fig. 12. Predicted LC of the tower crane for 70 years: (a) Jib length 60 cm, (b) Jib length 50 cm, (c) Jib length 40 cm, and (d) Jib length 30 cm.

Table 5. Predicted load charts (gram) for the prototype for 0 and 70 years.

Jib (cm)	Lifting radius (cm)														
	20	22	24	26	28	30	32	34	36	38	40	45	50	55	60
60	499.8	499.5	499.9	494.1	461.2	424.3	394.9	377.6	350.4	333.7	319.8	284.2	250.3	216.8	207.6
50	744.6	744.6	723.5	654.3	616.7	564.2	534.1	501.1	466.2	437.8	426.7	378.0	331.2		
40	938.5	851.6	783.2	716.8	661.1	607.2	578.5	534.7	508.4	471.9	455.3				
30	964.3	871.4	804.5	734.8	677.1	631.5									
Jib (cm)	Lifting radius (cm)														
	20	22	24	26	28	30	32	34	36	38	40	45	50	55	60
60	110.0	109.9	110.0	108.7	101.5	93.3	86.9	83.1	77.1	73.4	70.4	62.5	55.1	47.7	45.7
50	163.8	163.8	159.2	144.0	135.7	124.1	117.5	110.3	102.6	96.3	93.9	83.2	72.9		
40	206.5	187.4	172.3	157.7	145.4	133.6	127.3	117.6	111.9	103.8	100.2				
30	212.2	191.7	177.0	161.7	149.0	138.9									

Table 6. Predicted load charts (ton) for the real tower crane based on a scale factor for 0 and 70 years.

For 0-years:															
Jib	Lifting radius (m)														
(m)	20	22	24	26	28	30	32	34	36	38	40	45	50	55	60
60	11.9	11.9	11.9	11.8	11.0	10.1	9.4	9.0	8.4	8.0	7.6	6.8	6.0	5.2	4.9
50	17.8	17.8	17.3	15.7	14.8	13.5	12.8	12.0	11.1	10.5	10.2	9.0	7.9		
40	22.5	20.4	18.7	17.2	15.8	14.5	13.8	12.8	12.2	11.3	10.9				
30	23.1	20.9	19.3	17.6	16.2	15.1									
For 70-years:															

Jib	Lifting radius (m)														
(m)	20	22	24	26	28	30	32	34	36	38	40	45	50	55	60
60	2.6	2.6	2.6	2.6	2.4	2.2	2.1	2.0	1.9	1.8	1.7	1.5	1.3	1.1	1.1
50	3.9	3.9	3.8	3.5	3.3	3.0	2.8	2.6	2.5	2.3	2.3	2.0	1.7		
40	5.0	4.5	4.1	3.8	3.5	3.2	3.1	2.8	2.7	2.5	2.4				
30	5.1	4.6	4.2	3.9	3.6	3.3									

5.7. Validation

In order to account for the inherent unpredictability and variability in the experiment, a DTD model is applied to evaluate the degradation in LC of a tower crane using sample data. To validate the accuracy of the DTD model, a k-fold cross-validation approach is employed. The sample data is trained and predicted using SVM with k-5 cross-validation. The predictions demonstrate a high accuracy of 0.97 (R^2), comparable to that of a typical SVM model. Therefore, the proposed DTD model proves to be convenient, efficient, and based on real-time data, providing reliable results for predicting degradation in LC.

6. Discussion

This section presents the results of the DTD model, including the physical tower crane, virtual tower crane, IoT-based connection, data storage, and control system. Firstly, a scale-down tower crane prototype equipped with load cell and piezoelectric sensors was utilized to collect load and deflection data. The prototype also generated fundamental data considered at different stages of a DTD model. Previous approaches, such as analytical methods [67], non-destructive technologies [74], and numerical simulations [60, 65, 69], necessitated the use of hypothetical and artificial models to conduct experiments and determine failure mechanisms. Whereas data-driven models [23, 75] are data-intensive and need data for at least one year. Following the principle of similarity, the scaled model served as a substitute for the actual tower crane, enabling a realistic assessment of structural analysis, failure mechanism, dynamics, operation, and control process. For instance, Jiang et al. [25] used a tower crane prototype to investigate stability analysis and hoisting safety, while He et al. [52] used a prototype to study the impact of wind on cranes. The proposed DTD model offers several benefits over the existing methods, as it integrates a scaled model, sensors, and simulation data to predict degradation in LC.

Next, in the DTD model, the primary aim of the simulation is to replicate the lifting operation within a virtual environment. Consequently, adjustments, edits, updates, and calibrations can be made to the simulation of the virtual body until it aligns with the physical body in terms of LC. In our study, the load and deflection values were consistent between the physical and virtual cranes. However, there was a slight disparity in the material capacities of the physical and virtual bodies due to safety considerations on the construction site and experimental platform, as depicted in Fig. 13. A non-linear static analysis using ABAQUS was employed on a scaled model to calculate the material capacity as load/deflection, unlike load charts provided by manufacturing companies based on material properties. Nevertheless, a safety margin was incorporated into the construction or experimental platform to mitigate unforeseen failures. The collisions observed between the physical and virtual LC were

attributed to a factor of safety (FOS). In Fig. 13, the region under the blue line represents a safe/working zone, while it becomes a hazardous zone if it exceeds the blue line. The area under the red line denotes a damage zone, and beyond the red line indicates a failure zone, indicated in white. Although the physical and virtual data exhibited similar patterns, there were discrepancies in magnitudes. To address this, we quantified the degradation rate and integrated it with real-time data to reduce the magnitude and align the data from sensors and simulation [46, 61, 64, 65, 68, 76]. A similar approach was employed by Yang et al. [37], who multiplied wear data with a field-measurable precision index value. In summary, we developed a DTD model based on working loads and deflection. As working loads and deflection persist over several years, the material capacity will degrade due to residual stresses. Therefore, we calculated the residual stresses and incorporated them with operational values to predict degradation.

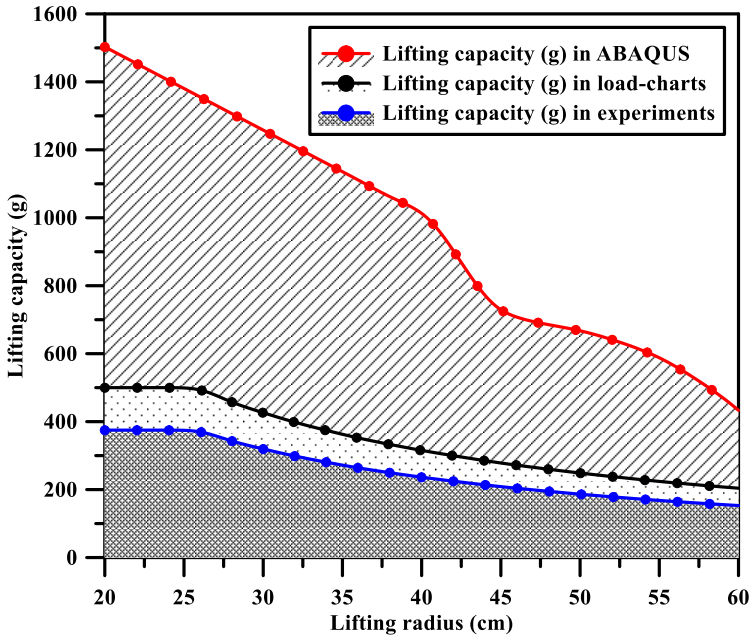


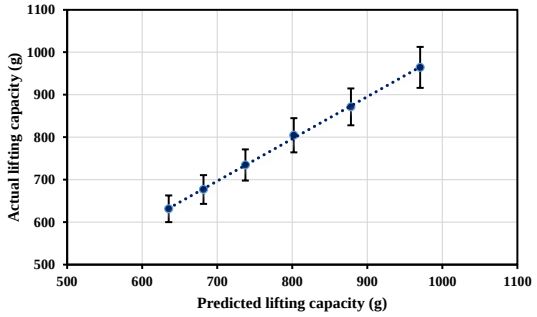
Fig. 13. Physical and virtual cranes load comparison and their zones.

Likewise, in a DTD model, the data flow is automated and stored in a real-time database. There is a bidirectional connection established between the virtual and physical cranes, unlike digital shadow, which lacks this capability [77]. Additionally, LC and degradation are influenced by various factors and described in different data formats with diverse and heterogeneous characteristics. Therefore, advanced data conversion technology is necessary to integrate and manipulate data from sensors, simulations, and fundamental sources in order to extract features relevant to LC and degradation. Moreover, all components of the proposed DTD model are integrated and mapped to detect and respond to real-time changes in the physical space, as well as to provide feedback to the control system. The secure connection and data transmission between the physical and virtual cranes, and vice versa, are also considered.

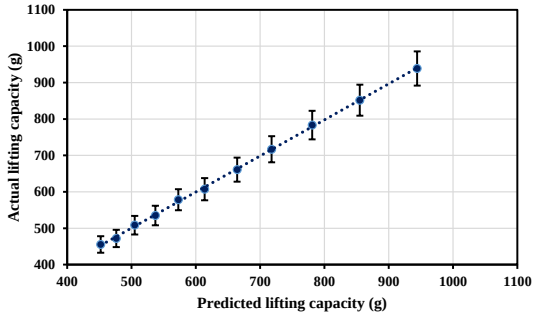
Lastly, the control system plays a crucial role in the DTD model by utilizing real-time data to predict degradation in LC. It operates in a hybrid mode and serves as the fundamental component responsible for analyzing and visualizing real-time changes, making informed

decisions, and providing feedback for further improvements. The control system performs essential tasks such as pre-processing, noise reduction, calibration, normalization, and raw and real-time data evaluation. It also incorporates feature recognition and selection. In DT technologies, it is crucial for the sensor and simulation data to align and encompass optimal parameters related to specific activities, as this integration and adjustment enhance prediction accuracy. In our study, we predicted the degradation in LC of a tower crane over a period of 70 years, presenting the results through graphs and load charts. Additionally, we utilized scaling and similarity factors to forecast degradation for various scaled-down jib lengths, including 30cm, 40cm, 50cm, and 60cm. In a related study, Roysson et al. [73] employed ANN for predicting the LC of a mobile crane, but the average deviation between the actual and predicted LC was 1.3. In our case, however, the average deviation between the actual and predicted LC is 2.6, indicating a higher level of deviation compared to previous research. This disparity can be attributed to our utilization of sensors, simulations, degradation rates, and six input parameters. In contrast, they relied on data solely from load charts and only three input parameters.

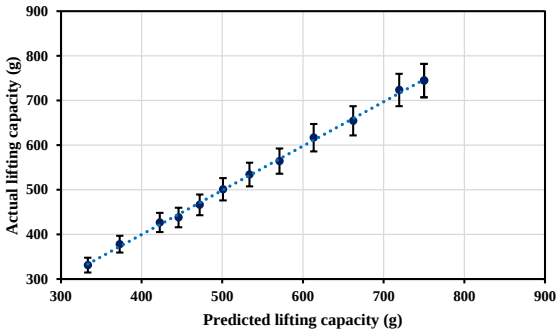
Similarly, Yang et al. [37] employed a DTD approach to predict performance degradation in the transmission unit of a CNC machine tool, achieving an average error of 4.33%. Our study utilized Mean Squared Error (MSE) and R-squared (R^2) as evaluation criteria for the DTD model. The prediction model yielded an MSE of 0.2253 and an R^2 of 0.9973. We compared the results with a traditional SVM model to validate our model, and the average prediction accuracy was nearly 99%. As illustrated in Fig. 14, the average deviation between the actual and predicted LC for scaled-down jib lengths of 30cm, 40cm, 50cm, and 60cm were 2.9, 2.6, 3.19, and 1.8, respectively. The overall average deviation across all jib lengths is 2.6. Additionally, in Fig. 15, we multiplied the scale factor of a prototype with the projected LC for jib lengths of 30cm, 40cm, 50cm, and 60cm, resulting in deviations of 0.04, 0.07, 0.06, and 0.07, respectively.



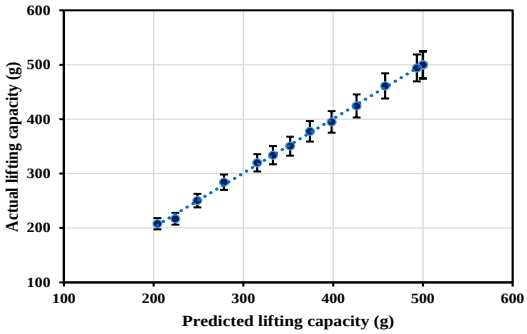
(a) Jib length 30 cm



(b) Jib length 40 cm

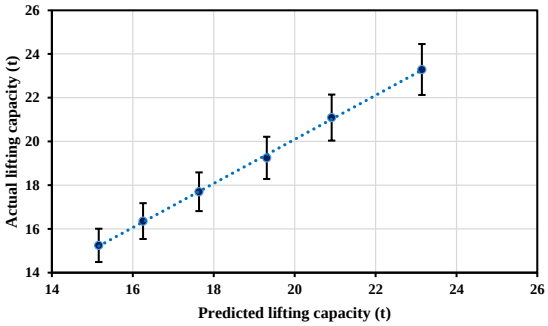


(c) Jib length 50 cm

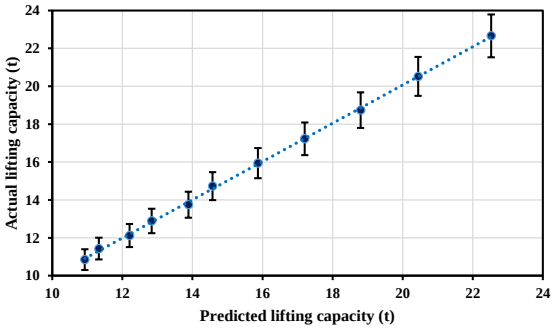


(d) Jib length 60 cm

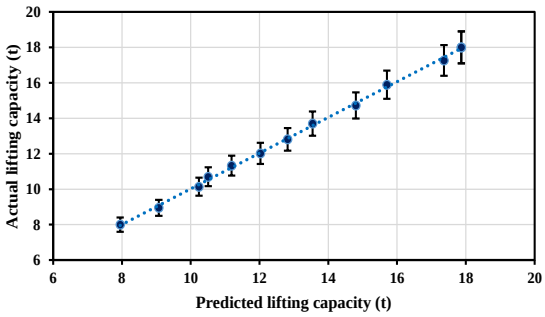
Fig. 14. Deviations between the actual and predicted LC for a scaled-down tower crane prototype: (1) Jib length 30cm, (b) Jib length 40cm, (c) Jib length 50cm, and (d) Jib length 60cm.



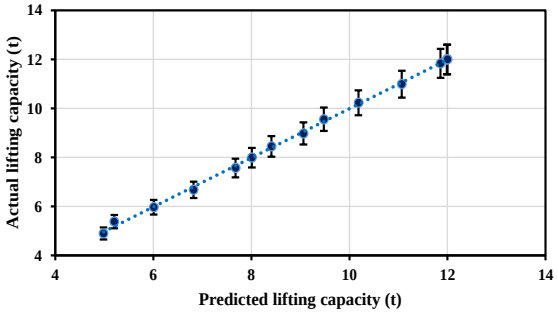
(a) Jib length 30 cm



(b) Jib length 40 cm



(c) Jib length 50 cm



(d) Jib length 60 cm

Fig. 15. Deviations between the actual and predicted LC for a real tower crane: (1) Jib length 30cm, (b) Jib length 40cm, (c) Jib length 50cm, and (d) Jib length 60cm.

7. Conclusion and Future Work

In order to mitigate the risk of structural fatigue and aging-induced deterioration leading to failure or collapse of construction tower cranes, this study developed a digital twin-driven (DTD) framework and model for predicting the degraded lifting capacities (LC) of aging tower cranes based on real-time load and deflection data. The DTD approach enables continuous monitoring of crane safety performance and real-time prediction of degraded LC using numerical models. The DTD model successfully predicted the LC of a scaled-down prototype tower crane with a jib length of 60cm for durations of 10, 20, 30, 40, 50, 60, and 70 years, achieving MSE and R^2 values of 0.2253 and 0.9973, respectively. Using scale and similarity

factors, the LC for actual tower cranes with jib lengths of 30m, 40m, 50m, and 60m was computed with an average deviation of 0.06%. This research contributes to understanding digital twin applications in the construction industry, particularly in predictive maintenance, aging infrastructure management, data-driven approaches, safety, reliability, and interdisciplinarity. The findings of this study also have broader applicability beyond the construction industry and can be implemented in other sectors facing similar infrastructure and predictive maintenance challenges.

While the results of this research are promising in predicting the degraded LC of aging tower cranes using the DTD approach, some areas can be further improved. Firstly, to enhance the simulation quality of the DTD model, future research should consider replicating the crane's foundation/baseplate, slewing unit, and climbing frame of an actual crane instead of relying on a prototype. Secondly, the precision of the LC prediction can be improved by incorporating a more comprehensive range of sensor types that capture various parameters. Thirdly, automating the connection system between virtual and physical cranes would enhance the efficiency of the DTD framework. Fourthly, it is recommended to identify the critical members through FEA of the truss-type structure rather than analyzing the overall crane structure. This can be achieved by considering detailed modeling and comprehensive analysis, resulting in a more focused and accurate assessment of the critical components. Lastly, considering the actual working conditions of the crane in numerical models can improve the accuracy of predicting degradation in LC.

Overall, this study highlights the potential of DTD approaches in enhancing the efficiency, safety, and decision-making related to aging tower cranes on construction sites. By providing a continuous monitoring system for crane safety, the DTD framework can assist operators in performing lifting operations with safe and degraded loads, thereby preventing unexpected failures and damages while improving workplace monitoring and safety. These findings present valuable opportunities for future research to advance the field further and enhance crane safety in construction sites.

Data availability statement

This paper contains all the data generated or analyzed during this study.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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1096