# Artificial intelligence-assisted civil engineering

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# ARTIFICAL INTELLIGENCE-ASSISTED CIVIL ENGINEERING: DIGITAL TWINS FOR THE WIND ENERGY INFRASTRUCTURE


### *Abstract*

In the landscape of contemporary Civil Engineering, Artificial Intelligence (AI) stands as a critical pillar of innovation, fundamentally transforming the operation and maintenance (O&M) of infrastructures systems. The present study focuses on the integration of AI to boost digital twins in addressing the complexities of life-cycle management of infrastructure assets. AI-boosted digital twins embody a synthesis of real-time data acquisition, advanced analytics, and predictive modelling, marking a significant departure from traditional O&M approaches that are often reactive and less informed. The methodology employed encapsulates the convergence of data and model twin-driven insights and computational intelligence, using environmental conditions to feed sophisticated probabilistic models and multi-physics simulations. This research specifically investigates the application of these technologies in the context of a case study on floating offshore wind turbines (FOWTs), yet the primary focus is the expansive role of AI-boosted digital twins across Civil Engineering domains. Significant findings from the study reveal the capability of AI-boosted digital twins to identify potential failure modes in structural components, predict the evolution of deterioration, and recommend timely O&M interventions in terms of different actions. In general, the present approach not only enhances the predictive accuracy of structural health assessments, but also optimizes resource allocation and minimizes downtime. By distilling the essence of these digital twins into actionable insights, the research underscores their potential to revolutionize infrastructure management. The implications are vast, heralding a new era of intelligent O&M strategies that promise increased safety, extended service life and cost-effectiveness. The integration of AI-boosted digital twins is posited to become an industry standard, advocating for a shift towards more resilient, adaptive, and intelligent Civil Engineering practices.



### *Keywords*

Civil Engineering Structures; Artificial Intelligence (AI); Digital Twins; Operation and Maintenance (O&M); Decision Making.


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# 1. INTRODUCTION

The next-generation civil infrastructure is on the cusp of a transformative era, with increasing demands for improved operation and maintenance (O&M) to ensure safety, efficiency, and sustainability. The escalating complexity of urban environments, coupled with aging infrastructure systems, necessitates a vital shift from traditional corrective maintenance to more proactive, predictive, and site-specific strategies. Advances in sensing technology, inspection methods, and simulation capabilities provide a solid foundation of reliable data and robust models, essential for understanding the current state, and in the mean time predicting future performance of Civil Engineering structures [1].

Sensing technologies have revolutionized the way infrastructure is monitored, employing a variety of tools such as fibre optics, drones, and wireless sensor networks to continually assess the condition of structures [2]. These technologies provide real-time data on various parameters, including stress, strain, vibration, and environmental effects, allowing for immediate detection of faults and potential issues [3]. Similarly, advanced inspection techniques, including non-destructive testing methods like ultrasonic pulse velocity and ground-penetrating radar, contribute to a more thorough and accurate assessment of the infrastructure health.

The rise of computational power and the development of sophisticated simulation methods have significantly enhanced the ability to model complicated civil infrastructure. These simulations, powered by finite element analysis, computational fluid dynamics, and other tools, enable engineers to predict the behaviour of structures under various conditions and loads, thus informing better design, maintenance, and operation decisions [4].

Amidst these technological advancements, the rapid growth of artificial intelligence (AI) has unlocked unprecedented possibilities for the digital twins [5] of Civil Engineering infrastructure. Especially, the innovation in AI sheds light on the emerging and promising concept of digital twins. Digital twins, are dynamic, virtual replicas of physical assets that provide a comprehensive and real-time view of their state and performance [6]. By integrating predictive analytics, continuous monitoring, and regular inspections, digital twins facilitate a more informed, efficient, and adaptive approach to O&M [7]. AI algorithms, ranging from machine learning to reinforcement learning, play a vital role in this integration, analysing massive data from sensors and inspections to detect patterns, predict failures, and plan O&M actions [8]. The implementation of AI-boosted digital twins represents a significant leap forward for the O&M of Civil Engineering projects. These systems not only enhance the precision and timeliness of maintenance interventions, but also extend the service life of assets, optimize resource allocation, and reduce the environmental impact of maintenance activities [9]. Furthermore, digital twins serve as a powerful tool for training and decision support, enabling engineers and maintenance personnel to explore various scenarios, assess the potential impact of different strategies, and make informed decisions based on comprehensive, up-to-date information [10]. Figure 1 illustrates a general framework of AI-boosted digital twins for wind turbines, integrating multiple facets of wind energy systems. In the module Resource & Loads, it depicts how AI interprets environmental data and load effects, crucial for optimizing the energy output and structural integrity. The module Infrastructure Resilience highlights the application of AI in predicting maintenance demands and life-cycle management, ensuring the durability and performance. The module Social Acceptance underscores the role of AI in harmonizing turbine integration within social landscapes, addressing public perception and environmental impacts. Central to the framework is the symbiotic relationship between the physical turbine and its digital counterpart, facilitated by AI, allowing real-time insights and virtualization to enhance operational efficiency and resilience.

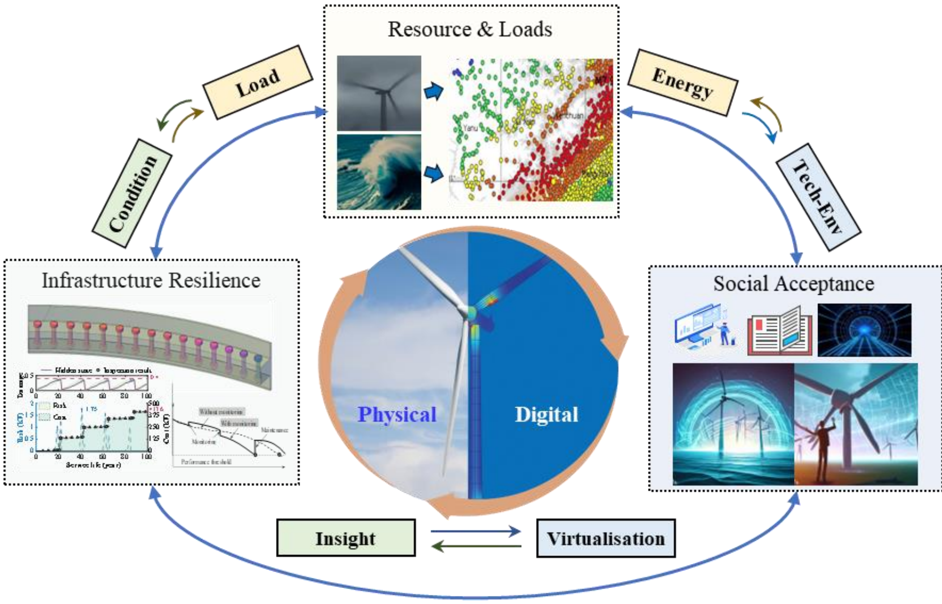


*Figure 1. A typical framework of AI-boosted digital twins of wind turbines.*

As stated above, the next-generation Civil Engineering infrastructure necessitates an enhanced, data-model integrated approach to O&M, driven by progresses in sensing, inspection, and simulation. The adoption of AI-boosted digital twins marks a key shift, potentially revolutionizing infrastructure O&M. This paper aims to elucidate the role and potential of Artificial Intelligence (AI)-boosted digital twins in enhancing the operation and maintenance of civil engineering structures. It begins by delineating the digital twins in general from three aspects, including the forward digital twins, backward digital twins, and digital twins-informed decision making. Then, a case study is illustrated in terms of the forward digital twins in wind turbine structures, in order to offer a brief glimpse over the state-of-art application and benefits. The paper concludes with insights into future directions and the broader implications of this technology.

## 2. GENERAL PERSPECTIVES OF AI-BOOSTED DIGITAL TWINS

### 2.1. FORWARD DIGITAL TWINS

The detailed depiction of forward digital twins, as exhibited in Figure 2, includes a comprehensive process that starts with the real-time acquisition of data directly from engineering structures and progresses methodically towards an advanced assessment of structural health state. This framework serves as a testament to the seamless confluence of several high-tech methodologies: from environmental monitoring that continuously tracks external conditions affecting the structure to sophisticated data analysis techniques that digest and interpret complicated datasets. The predictive modelling component of this framework is particularly crucial that it utilises advanced algorithms and simulation techniques to forecast potential structural issues. Within this framework, the analysis of collected data involves an interpretive process that can discern patterns indicative of potential failures. This is supported by the predictive modelling aspect, where the data informs simulations that replicate the structural behaviour under various scenarios. The models are crafted to reflect the true nature of the materials, the physics governing the structure, and the environmental interactions.

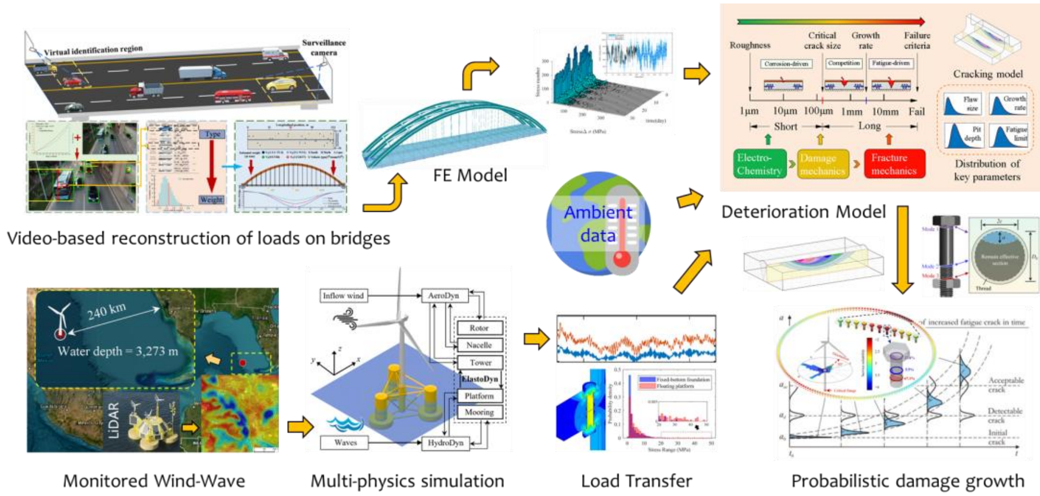


*Figure 2. Forward digital twins from condition perception to state assessment.*

Delving into broader perspectives, forward digital twins of engineering structures represent a critical shift in structural condition assessment. The application of forward digital twins introduces a proactive model that combines the site-specific real-time monitoring with the foresight of simulation [11]. Leveraging cutting-edge sensor technologies, these systems continuously collect data on structural behaviour and external environmental conditions. The data are then processed using advanced simulation models that are able to predict the structural response to various stimuli and forecast potential degradation pathways [12]. The core of the forward digital twins approach lies on its ability to simulate future states of the structure based on current conditions. By employing algorithms rooted in different disciplines such as computational mechanics, material science, electrochemistry, etc., these digital replicas can evaluate structural behaviour, anticipate material degradation, and predict the service of components and structural systems [13]. In general, forward digital twins serve as a pivot of interdisciplinary data, enabling an inclusive view of the structural health. Through the integration of AI algorithms, these systems can improve their predictive capabilities over time, learning from available historical data to improve the efficiency of forecasts [14]. This continual learning loop not only increases the reliability of condition assessments but also enhances the adaptability of the digital twins to evolving structural complexities and changing environmental factors.

## 2.2. BACKWARD DIGITAL TWINS

As a counterpart to the prediction-oriented forward digital twins, the backward digital twins serve for a prognostic function for Civil Engineering structures. These digital twins are instrumental in the synthesis of prediction and inspection results, forging a comprehensive understanding of the structures from an as-operated standpoint. The backward framework of digital twins is rooted in the convergence of prediction models and inspection results. Apart from the integration of prediction models and monitoring data, it typically incorporates historical data from periodic and/or nonregular inspections [15]. Unlike forward digital twins that primarily focus on future state predictions, backward digital twins emphasize the diagnostic analysis of the structure at first, which further are able to support the updated prediction. Figure 3 illustrates a typical framework of backward digital twins in case of wind turbine structures. The procedure begins with the assimilation of data into a central repository (e.g., the model) where the observed conditions of the structure are aligned with its corresponding digital representation. Sophisticated algorithms, such as Physics-Informed Neural Networks (PINNs) [16] combined with Dynamic Bayesian Networks (DBNs) [17] are then utilized to analyse the relationship between the state, response, and measurement to update the *a priori* model into an *a posteriori* counterpart. This analytical approach ensures updated understanding of structural behaviours in an *a priori-to-a posteriori* manner, which encompasses identifying discrepancies between predicted models and actual observations.

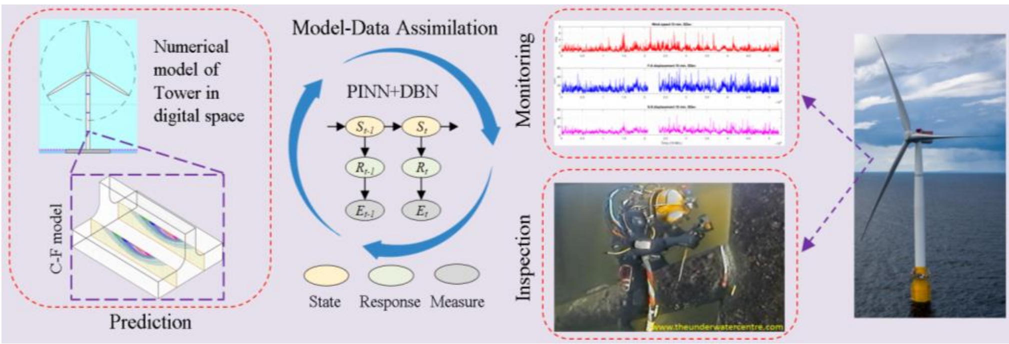


*Figure 3. Backward digital twins to integrate prediction and inspection results.*

In practice, backward digital twins excel in their ability to uncover patterns and damage that may not have been immediately apparent through standard monitoring techniques. For instance, the analysis may reveal that certain structural responses under specific environmental conditions diverge from predicted behaviours. Such insights are highly-valued, as they prompt a re-check of the predictive models and, possible adaption to the digital twin to better reflect the exact structural behaviour. Moreover, by fusing inspection data, backward digital twins enrich the database. For example, an inspection may reveal early signs of damage not yet captured by sensors, prompting an update to the digital twin to account for such factors. Backward digital twins, therefore, represent a feedback mechanism that perpetually refines the structural model.

## 2.3. DIGITAL TWINS-INFORMED DECISION MAKING

As discussed above, the forward and backward digital twins can offer comprehensive insights into the current health state and future evolution of Civil Engineering structures. On this basis, a well-informed decision making can be carried out to optimise O&M strategies [18]. The core to this optimization lies on the delicate equilibrium between mitigating risks and minimizing costs, achieved through the intelligent interpretation of model and data twin-driven insights. As depicted in Figure 4, digital twins-informed decision-making operates on a dynamic feedback loop paradigm. This loop begins with the digital twin seizing the initial state (State 0) of the structure, followed by the execution of an action, often a maintenance intervention or operational adjustment, which then leads to a new state (State 1). The consequence of this action, whether positive or negative, is considered a reward or penalty in the context of reinforcement learning [19], guiding the next set of actions to be taken.

Decision-making in this context is not only about choosing the right action, but also determining the optimal timing (When), identifying the most critical maintenance needs (What), and selecting the most effective intervention methods (How) [20]. These decisions are driven by the capacity of digital twins to project the future condition of the structure based on its current state and to simulate various scenarios and outcomes of different actions. The optimisation planning component is where the intelligence of digital twins is fully leveraged. Utilizing the insights gained from both forward and backward digital twins, owners can plan maintenance schedules, allocate resources effectively, and prepare for future challenges. Through a scenario simulation, they can explore the consequences of different decisions, finding the most cost-effective approach while maintaining a low risk of structural failure. Thus, digital twins-informed decision-making is the intelligent pivot where data, prediction, and past experiences converge to provide a strategic approach to O&M. It embodies a sophisticated method of managing Civil Engineering structures, where every action is evidence-based, every strategy is risk-averse, and every decision aims to extend the lifespan of the infrastructure ensuring in the mean time safety and functionality. This vital shifts towards a more informed, proactive, and data-centric O&M strategy is a game changer in the management of Civil Engineering structures, leading to enhanced longevity, resilience, and performance of the built environment.

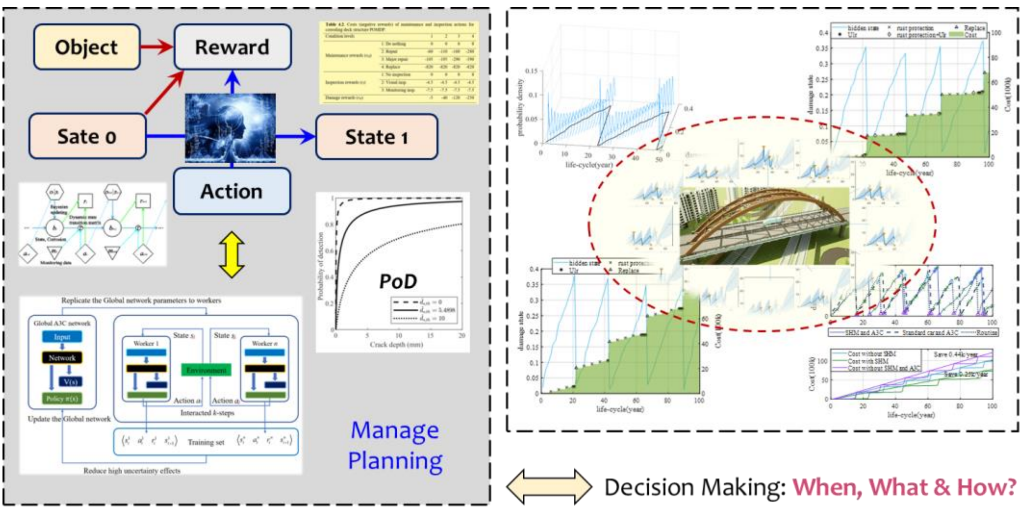


*Figure 4. Digital twins-informed decision making of O&M policies.*

## 3. A CASE STUDY OF FLOATING OFFSHORE WIND TURBINES

The drive towards a sustainable and eco-friendly future, fuelled by the pressing climate issues and the escalating need for energy, has accelerated the quest for renewable and dependable energy sources. The innovative concept of the modular energy island (MEI) [21] has been introduced to harness the copious natural resources available in the depths of the oceans, such as wind, tidal, and solar energy. This pioneering approach, however, introduces unique engineering challenges. Among these is the heightened vulnerability of the substantial high-strength bolts located in the ring-flange connections of wind turbine towers to corrosion-fatigue (CF) degradation [22]. This study seeks to shed light on the CF deterioration mechanisms affecting the bolts in floating offshore wind turbines

(FOWTs) on MEIs. It does so by amalgamating material testing data, environmental conditions specific to the site, a probabilistic CF (PCF) model, and advanced multi-physics simulations.

The study involves the assimilation of wind-wave data from the Gulf of Mexico [23] into the multi-physics simulation tool OpenFAST [24]. As shown in Figure 5, the data are then processed by the PCF model to predict the deterioration evolution of the structure. The assessment emphasizes the stochastic nature of CF and leverages material test data and site-specific conditions to enhance the precision of the analysis. Figure 6 delineates the progression of fatigue crack growth in the most critical bolts located at the bottom flange. The analysis reveals the predominance of Mode-3 failure, which corresponds to the first engaged threads, as a major vulnerability, accounting for a significant 74.7% of the failure probability. While Modes 1 and 2 represent a smaller fraction of failure risk, at 20.3% and 5.0% respectively, their potential impact on bolt integrity is nonetheless noteworthy. The data suggests that, over time, the propensity for crack depth in the high-strength bolts to increase is pronounced, with the distribution indicating a steady approach towards a critical threshold of 46.8 mm with the service time.

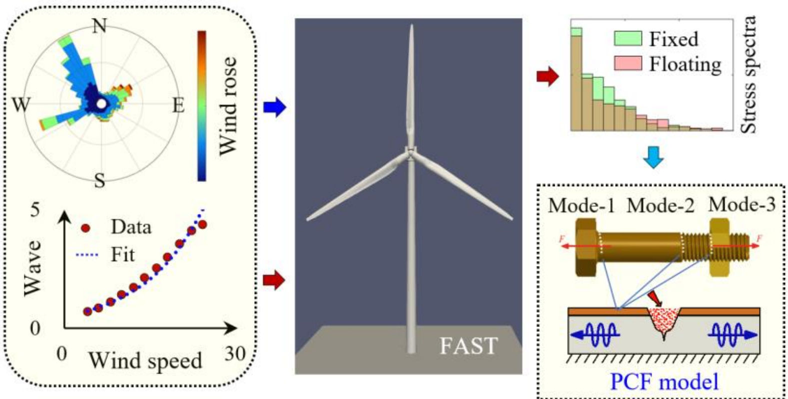


*Figure 5. Probabilistic deterioration assessment of FOWT structures by forward digital twins.*

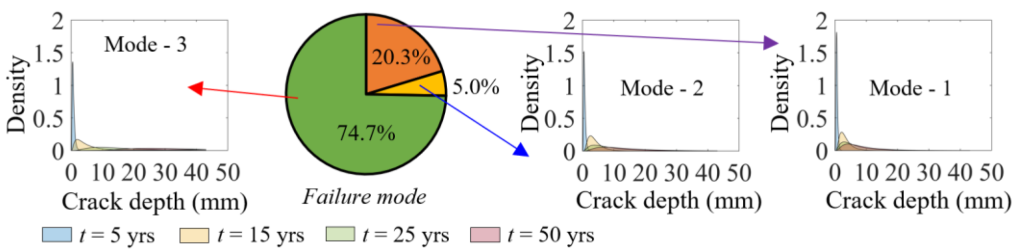


*Figure 6. Fatigue crack depth growth and failure modes of the most critical bolt in ring-flanges.*

The threshold signifies a point of concern, beyond which the likelihood of bolt failure escalates dramatically. The density plots for different time intervals show a trend where the crack depth begins to stabilize and concentrate around the critical size, especially as the service life extends towards the 20-year mark. This suggests that the first engaged threads show a higher incidence of fatigue crack initiation and propagation compared to the other modes. The findings depicted in this figure emphasize the necessity for vigilant monitoring and proactive maintenance strategies, particularly focused on the first engaged threads of the bolts, to prevent the progression of fatigue cracks to the critical threshold. This approach is essential to ensure the structural integrity and longevity of FOWTs, highlighting the importance of prioritising maintenance activities that target the identified high-risk failure modes.

# 4. CONCLUSIONS

Based on the above efforts and discussions, a list of major findings can be drawn as the following.

- AI-boosted digital twins have emerged as a transformative solution for the operation and maintenance (O&M) of Civil Engineering structures, providing a proactive and predictive approach that is vital in the face of aging infrastructure exposed to complex service conditions.
- Advances in sensing technologies and inspection methods, along with simulation capabilities, have enabled a robust and reliable framework for understanding, predicting and managing the performance of Civil Engineering structures via AI-boosted digital twins.
- A case study on the modular energy island (MEI) concept demonstrated the capacity of forward digital twins to predict corrosion-fatigue (CF) deterioration in high-strength bolts within wind turbine towers, highlighting the importance of integrating prediction model, material data and monitored site-specific conditions into probabilistic simulations.
- The insights gained from this work advocate for a prediction-monitoring-inspection integrated framework and a proactive O&M methodology that prioritises high-risk failure modes to ensure structural integrity, functionality and durability.

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