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# Artificial Intelligence-Powered Digital Twins for Sustainable and Resilient Engineering Structures

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**Abstract** Artificial Intelligence (AI) is now playing a crucial role not only in everyday life, evidenced by the booming application of Large Language Models (LLMs) such as the Generative Pretrained Transformer (GPT), but also in its potential to transform traditional industries like civil engineering. This work examines the application of novel AI tools to enable Digital Twins (DT) for engineering structures, providing a comprehensive solution for the life-cycle management. A comprehensive state-of-the-art review is conducted to explore existing advancements in sensing, inspection, and simulation that are fundamental to the development of digital twins. Building on this knowledge, a framework is proposed to define DT for Engineering (DT4ENG) based on their emphasis and data flow, including forward DT, backward DT, and DT-informed decision making. Following this, a case study on floating offshore wind turbine (FOWT) structures demonstrates the application of DT4ENG in a specific domain, with findings that have broader implications for the life-cycle management of engineering structures. The present study reveals that the AI effectively enables digital twins to identify potential structure issues, predict deterioration, and suggest timely maintenance interventions. This approach enhances the accuracy of structural health assessments, optimises resource allocation, and minimises downtime. By translating the capabilities of digital twins into actionable strategies, the research highlights their potential in the significant improvement of the life-cycle management of engineering infrastructure. In general, these advancements promise a new era of intelligent maintenance strategies, offering increased safety, extended service life, and cost-effectiveness. The proposed DT4ENG is set to become a standard in the traditional industry, driving a shift towards more sustainable, resilient, adaptive, and intelligent structures.

**Keywords** Engineering Structures; Artificial Intelligence; Digital Twins for Engineering (DT4ENG); Intelligent Maintenance; Floating Offshore Wind Turbine (FOWT).

## 1 Introduction

The next-generation engineering structure is on a key turning point, with increasing demands for improved life-cycle design, construction and maintenance to ensure safety, efficiency, sustainability and resilience. The growing complexity of environments, coupling with aging infrastructure systems, underscores a shift from traditional open-loop methods to more proactive, predictive, and site-specific strategies. Advances in sensing technology, inspection methods, and simulation capabilities provide a robust foundation of reliable data and models, which are essential for understanding the current state and predicting the future performance of civil engineering structures [1]. For instance, Sensing technologies have improved infrastructure monitoring by using tools such as fibre optics, drones, and wireless sensor networks, which continuously assess structural conditions [2]. These technologies offer online data collection on stress, strain, vibration, and environmental effects, allowing for immediate fault identification [3]. Advanced inspection techniques like ultrasonic pulse velocity and ground-penetrating radar further enhance infrastructure health assessments. Contact-less measurement methods, including visual inspection systems with convolutional neural networks, have significantly improved the accuracy and efficiency of structural assessments[4][5]. The rapid development in computational power and advanced simulation methods has greatly enhanced the modelling of complex civil infrastructure. Simulations powered by finite element analysis and computational fluid dynamics allow engineers to predict structural behaviour under various conditions [6]. Structural control, particularly in vibration control, has advanced through vibration-based energy harvesting, providing benefits in energy efficiency and structural stability [7]. More important, the growth of artificial intelligence (AI) has enabled new possibilities for Digital Twins for Engineering (DT4ENG). Digital twins [8] are dynamic, virtual replicas of physical assets, providing real-time views of their state and performance [9]. By integrating predictive analytics, continuous monitoring, and regular inspections, DT4ENG supports a more informed and adaptive maintenance approach [10]. Within the core of the DT4ENG lies the Artificial Intelligence (AI) algorithm, e.g. machine learning, deep learning, reinforcement learning, etc., which analyse data from sensors and inspections to detect patterns, predict failures, and plan maintenance actions [11]. To this end, DT4ENG represents a significant advancement for civil engineering maintenance. These systems enhance the precision and timeliness of maintenance interventions, extend asset service life, optimise resource use, and reduce the eco-impact of maintenance actions [12]. Additionally, DT4ENG serves as a tool for training and decision support, allowing engineers to explore scenarios, assess strategy impacts, and make well-informed decisions with up-to-date information and sufficient what-if simulations [13]. Specifically, ageing infrastructure is particularly vulnerable to deterioration, which can compromise structural integrity and safety [14]. Various efforts have highlighted the importance of predictive maintenance strategies in extending the lifespan of such structures. Especially, factors like corrosion-fatigue and dynamic loads contribute significantly to the degradation of structural components, emphasising the need for advanced diagnostic and predictive tools to manage these issues effectively [15][16].

Figure 1 shows a framework for the DT4ENG in case of wind turbines, integrating multiple facets of wind energy systems. The resource and loads module illustrate how AI interprets environmental data and load effects, essential for optimising energy output and structural integrity. The infrastructure resilience module highlights the role of AI in proactive maintenance demands and life-cycle management, ensuring serviceability, durability and safety. The social acceptance module emphasises the AI in integrating turbines within social concerns, addressing public perception and eco-impacts. Central to the framework is the relationship between the physical turbine and its digital counterpart, facilitated by AI, which enhances operational efficiency and resilience.

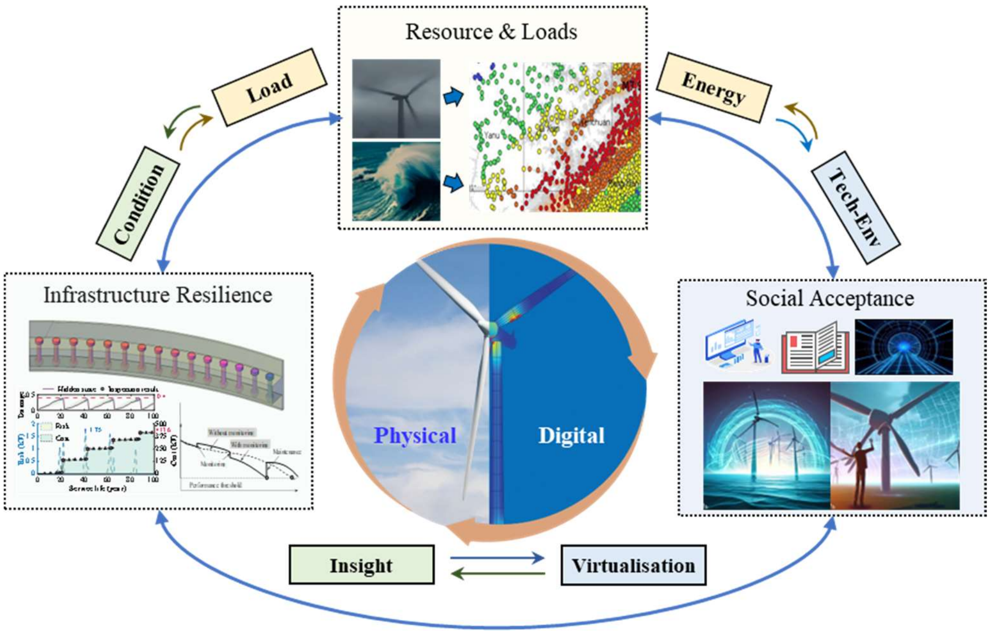



**Figure 1** A typical framework of DT4ENG in wind turbines.

As discussed above, the future engineering structure, especially the wind turbine structure, demands an enhanced, data-model integrated approach to life-cycle management, driven by advancements in sensing, inspection, and simulation technologies. The application of DT4ENG signifies a pivotal shift that has the potential to revolutionise the management of infrastructure assets. This work explores the role and potential of AI-enhanced DT4ENG in improving the maintenance of civil engineering structures. It begins by detailing digital twins from three perspectives: forward DT, backward DT, and DT-informed decision making. Following this, a case study on forward DT in floating offshore wind turbine structures is presented, providing a snapshot of state-of-the-art applications and their benefits. Finally, the work concludes with insights into future directions and the broader implications of this transformative technology.

## 2 General Perspectives of DT4ENG

### 2.1 Forward Digital Twins

Forward DT represents a cutting-edge approach in engineering maintenance, combining real-time data acquisition with advanced simulations and predictive analytics. This novel method enhances structural serviceability, sustainability and resilience by providing a continuous, comprehensive view of a structural current condition and future performance. The detailed depiction of forward digital twins, as shown in Figure 2, outlines a comprehensive process beginning with the real-time data acquisition directly from structures and advancing towards an improved assessment of structural health state. This framework exemplifies the integration of multiple advanced methodologies, from site-condition monitoring that continuously tracks external conditions affecting the structure to sophisticated data analysis techniques that interpret complex datasets. The process starts with the collection of site-condition data, including wind and wave measurements, using technologies like LiDAR (Light Detection and Ranging) and other sensors. These monitoring data is fed into multi-physics simulation tools, which simulate interactions between various components of the wind turbine under environmental excitations. The results from the above simulations are processed with load transfer from the structure to component, and then to the detail, by analysing stress ranges and distributions. Following the load analysis, a deterioration model is applied to predict structural deterioration over time, considering factors such as material roughness, critical crack size, growth rates, and failure criteria. This model integrates multiple disciplines like electrochemistry, damage mechanics, and fracture mechanics. Finally, probabilistic models predict the growth of damage over time, simulating the growth of cracks and assessing the likelihood of different failure modes, accounting for uncertainties in material properties, environmental conditions, and operational loads.

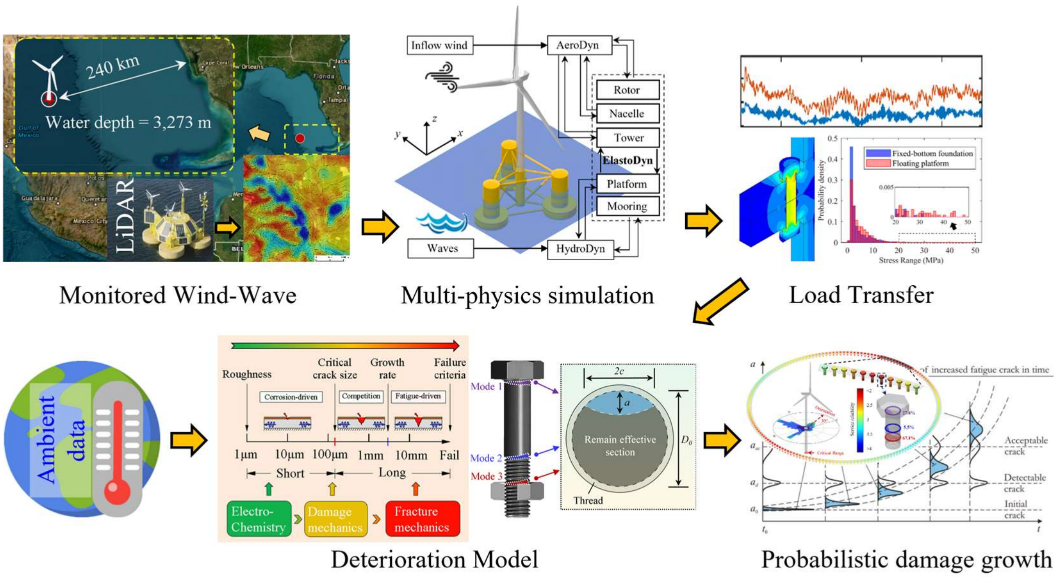



**Figure 2** Forward digital twins from condition perception to state assessment.

In general, forward DT of engineering structures signifies a rudimentary shift in structural condition assessment by introducing a proactive model that combines site-specific real-time monitoring, numerical simulations and prediction models [17]. Utilising state-of-the-art sensing technologies, these systems continuously collect data on structural behaviour and site-conditions, which is processed by using advanced simulation models and algorithms to predict responses to various excitation and envisage possible deterioration modes [18]. The core of forward DT lies in its ability to simulate future states based on current conditions, employing algorithms like computational mechanics, material science, and electrochemistry to evaluate structural behaviour, anticipate degradation, and predict service life [19]. Through the further integration of AI algorithms, these systems enhance predictive capabilities over time by learning from historical data, thus improving prediction efficiency [20]. This active learning manner not only increases the reliability of condition assessments but also enhances the adaptability of DT to the changing environment.

## 2.2 Backward Digital Twins

In contrast to the prediction-focused forward DT, backward DT perform a prognostic function for structures. These DTs are crucial for synthesising prediction and inspection results, thereby providing a comprehensive understanding of structural conditions. The backward DT is founded on the convergence of prediction models, inspection result and monitoring data. Besides integrating prediction models and monitoring data, it typically includes historical data from periodic and non-regular inspections [21]. Unlike forward digital twins, which primarily predicts future states, backward digital twins initially focus on diagnostic analysis, which then informs and supports updated predictions. As illustrated in Figure 3, the backward DT for wind turbine structures begins with model-data integration, where observed structural conditions are aligned with their digital replica. This process involves continuous monitoring and periodic inspections. Advanced algorithms, such as Physics-Informed Neural Networks (PINNs) [22] and Dynamic Bayesian Networks (DBNs) [23], can be employed to analyse the relationships between state, response, and measurement, updating the a priori model into an a posteriori counterpart. Accordingly, this model-data integrated approach provides an updated understanding of structural behaviours and integrity by identifying differences between model predictions and exact observations and/or measurements.

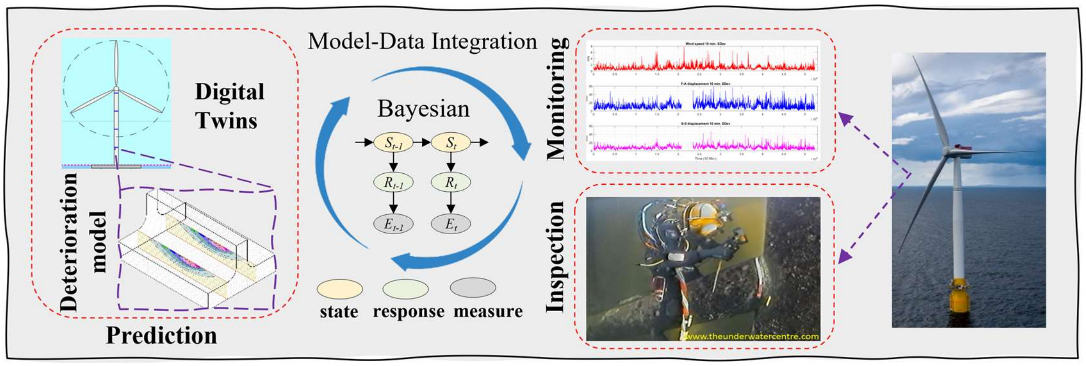


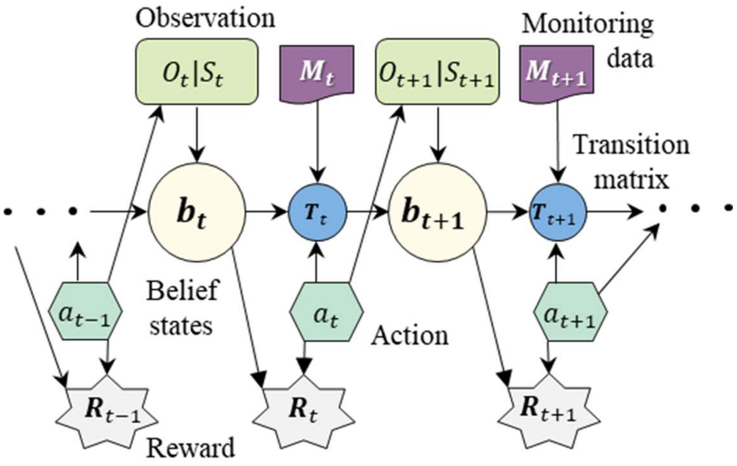

**Figure 3** Backward DT to integrate model prediction, inspection results and monitoring data.

As discussed above, the backward DT is particularly effective in identifying patterns and damages that might not be immediately visible through conventional monitoring techniques. These analyses can uncover inconsistencies between expected and actual structural responses and observations under various environmental conditions. Such results are crucial as they prompt a re-examination of the predictive models and may lead to necessary adjustments in the DT to mirror the structural state and behaviour accurately. Additionally, by integrating inspection data, backward DT expands the database. Inspections can reveal early signs of damages that sensors may have missed, requiring updates to the DT to account for these findings. Therefore, backward DT acts as a dynamic feedback system, continually enhancing the accuracy of the structural model.

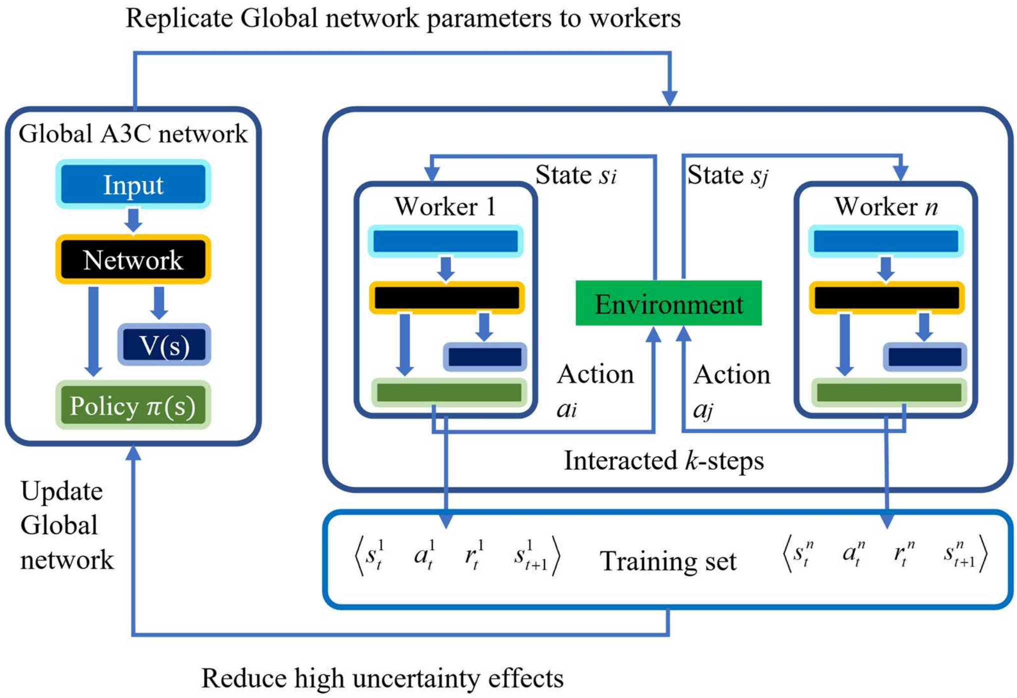
### 2.3 Digital Twins-Informed Decision Making

In general, the forward and backward DT provide in-depth insights into the current condition and anticipated evolution of engineering structures. These insights enable informed decision-making to optimise maintenance policies [24]. The essence of this type of optimisation lies in striking a balance between risk mitigation and cost reduction, achieved by the intelligent interpretation of insights derived from both model and data. Figure 4 illustrates the core engine of this process, including a dynamic POMDP (Partially Observable Markovic Decision Process, shown in Figure 4a), and reinforcement learning with muti-agent (shown in Figure 4b) to support the solution of the dynamic POMDP. The dynamic POMDP begins with an initial state of the structure, followed by an action, such as a maintenance intervention or operational adjustment, which then transits the structure to a new state. The outcome of this intervention, whether beneficial or detrimental, serves as a reward or penalty within a reinforcement learning framework, guiding the selection of subsequent actions. The reinforcement learning framework [25] involves a Global A3C network that replicates its parameters to multiple worker agents. Each worker interacts with the environment, taking actions and receiving states and rewards. These interactions are recorded in a training set, which is used to update the global network, reducing the effects of high uncertainty.

In this context, the decision-making is not only about selecting 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) [26]. The DT projects the future condition of the structure based on its current state and simulate various scenarios to predict the outcomes of different actions. The optimisation planning component leverages the intelligence of DT. By utilising insights from both forward and backward DT, owners can develop maintenance schedules, allocate resources effectively, and prepare for future challenges. Scenario simulations allow exploration of different decision outcomes, identifying the most cost-effective strategies while maintaining a low risk of structural failure.




(a) Dynamic POMDP.




(b) Reinforcement learning with muti-agent.

**Figure 4** Engine for DT-informed decision making: (a) Dynamic POMDP; (b) Reinforcement learning with muti-agent.

In general, the above DT-informed decision-making combines data, predictions, and historical experiences to provide a strategic approach to maintenance. This method represents a sophisticated approach to managing structures, ensuring that every action is evidence-based, every strategy is risk-averse, and every decision aims to extend the lifespan while ensuring safety and functionality. This shift towards a more informed, proactive, and data-centric maintenance strategy is transformative in the infrastructure management, leading to enhanced longevity, resilience, and performance.

## 3 Digital Twins-boosted deterioration prognosis of floating offshore wind turbine structures: a case study

To illustrate the practical application and benefits of DT4ENG, a detailed case study is presented in this section, focusing on the corrosion-fatigue (CF) deterioration of high-strength bolts in the ring-flange connections of floating offshore wind turbines (FOWTs) on modular energy islands (MEIs) [27]. The MEI is designed to harness the abundant natural resources found in ocean depths, such as wind, tidal, and solar energy. However, this pioneering approach presents unique engineering challenges, including the increased susceptibility of high-strength bolts in the ring-flange connections of wind turbine towers to corrosion-fatigue (CF) deterioration [28]. According, the case study has been carried out to elucidate the CF deterioration mechanisms affecting bolts in floating offshore wind turbines (FOWTs) on MEIs by integrating material testing data, site-specific environmental conditions, a probabilistic CF (PCF) model, and advanced multi-physics simulations. The research incorporates wind-wave data from the Gulf of Mexico [29] into the multi-physics simulation tool OpenFAST [30]. As illustrated in Figure 5, this data is processed through the PCF model to predict the structural deterioration evolution. The assessment highlights the stochastic nature of CF, leveraging material test data and site-specific conditions to improve analysis accuracy.

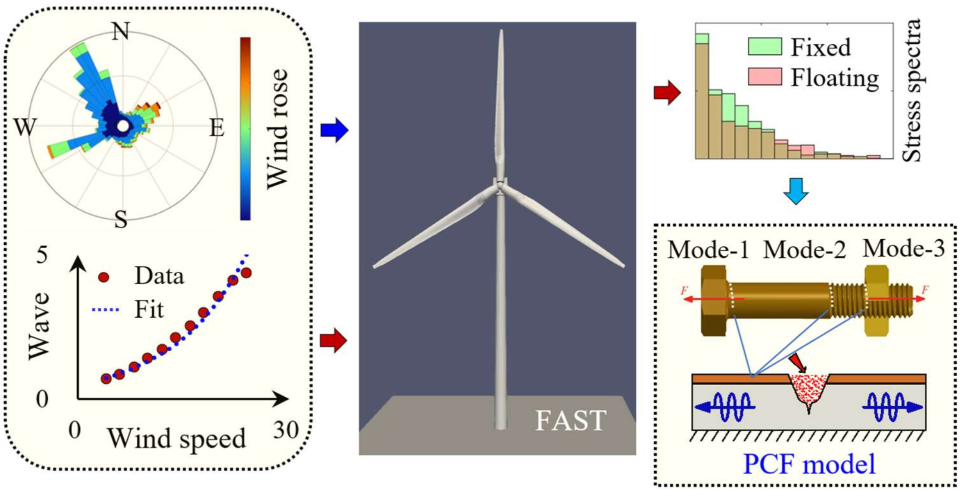



**Figure 5** Probabilistic deterioration assessment of FOWTs by forward DT.

Figure 6 depicts the progression of fatigue crack growth in the most critical bolts at the bottom flange. The analysis identifies Mode-3 failure, related to the first engaged threads, as a major vulnerability, constituting 74.7% of the failure probability. Modes 1 and 2 account for 20.3% and 5.0% of the failure risk, respectively, indicating their significant impact on bolt integrity. This also indicates a higher incidence of fatigue crack initiation and propagation in the first engaged threads compared to other modes. Over time, the distribution of crack depth is shifting rightward to a critical threshold of 46.8 mm as service time progresses. This threshold represents a point of concern where the probability of bolt failure sharply increases. Meanwhile, the density plots for different time intervals reveal that crack depth tends to stabilise and concentrate around the critical size, especially as the service life nears 20 years. These findings underscore the necessity for online monitoring and proactive maintenance strategies, particularly focusing on the first engaged threads of the bolts, to prevent fatigue cracks from reaching the critical threshold.

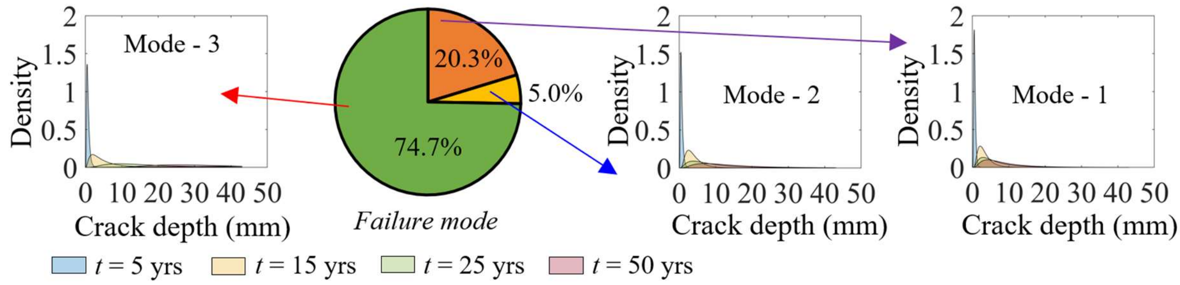



**Figure 6** Crack growth and failure modes of the most critical bolt in ring-flange connections.

## 4 Conclusion

Based on the above efforts and discussions, several major findings can be drawn.

- The AI boosts Digital Twins for Engineering (DT4ENG), which emerges as a transformative solution for life-cycle management of engineering structures. This provides a proactive and predictive approach that is crucial for addressing the challenges posed by aging infrastructure exposed to complex service conditions.
- Advances in sensing technologies, inspection methods, and simulation capabilities have established a robust and reliable framework. This framework is essential for understanding, predicting, and managing the performance of engineering structures through DT4ENG.
- A case study on the modular energy island (MEI) concept demonstrates the effectiveness of DT4ENG in predicting corrosion-fatigue (CF) deterioration in floating offshore wind turbines. The study highlights the importance of integrating predictive models, material data, and monitored site-specific conditions into probabilistic simulations.
- The insights gained from this work advocate for an integrated prediction-monitoring-inspection framework. This approach supports a proactive maintenance methodology that prioritises high-risk failure modes, ensuring the structural integrity, functionality, and durability.

While the integration of DT4ENG shows great promise, there are still challenges to overcome, including the high initial setup costs, the need for continuous data acquisition and processing, and the complexity of integrating various data sources and models. Future efforts are highly suggested on developing more cost-effective solutions for deploying DTs, enhancing the interoperability of different systems and data formats, and advancing machine learning algorithms to improve accuracy and efficiency. Additionally, integrating the DT with emerging technologies such as the Metaverse, mixed reality, and smart robots are also highly motivated to enhance real-time monitoring, immersive visualisation, and automated management.

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**Literature**

[1] Hassani, S., & Dackermann, U. (2023). A Systematic Review of Advanced Sensor Technologies for Non-Destructive Testing and Structural Health Monitoring. Sensors, 23(4), 2204.
[2] Jayawickrema, U. M. N., Herath, H. M. C. M., Hettiarachchi, N. K., Sooriyaarachchi, H. P., & Epaarachchi, J. A. (2022). Fibre-optic sensor and deep learning-based structural health monitoring systems for civil structures: A review. Measurement, 199, 111543.
[3] Lynch, J. P., & Loh, K. J. (2006). A summary review of wireless sensors and sensor networks for structural health monitoring. The Shock and Vibration Digest, 38(2), 91-130.
[4] Jiang, T., Frøseth, G. T., Rønnquist, A., Kong, X., & Deng, L. (2024). A visual inspection and diagnosis system for bridge rivets based on a convolutional neural network. Computer-Aided Civil and Infrastructure Engineering, 1–19.
[5] Jiang, T., Frøseth, G. T., Wang, S., Petersen, Ø. W., & Rønnquist, A. (2024). A 6-DOF camera motion correction method using IMU sensors for photogrammetry and optical measurements. Mechanical Systems and Signal Processing, 210, 111148.
[6] Bazjanac, V. (2008). Building energy performance simulation as part of interoperable software environments. Building Simulation, 1(2), 97-110.
[7] Cai, Q., & Zhu, S. (2022). The nexus between vibration-based energy harvesting and structural vibration control: A comprehensive review. Renewable and Sustainable Energy Reviews, 155, 111920.
[8] Jiang, F., Ma, L., Broyd, T., & Chen, K. (2021). Digital twin and its implementations in the civil engineering sector. Automation in Construction, 130, 103838.
[9] Piascik, R., Vickers, J., Lowry, D., Scotti, S., Stewart, J., & Calomino, A. (2010). Technology area 12: Materials, structures, mechanical systems, and manufacturing road map. NASA Office of Chief Technologist, 15-88.
[10] Grieves, M. (2014). Digital twin: Manufacturing excellence through virtual factory replication. White paper, 1(2014), 1-7.
[11] Canizo, M., Onieva, E., Conde, A., Charramendieta, S., & Trujillo, S. (2017, June). Real-time predictive maintenance for wind turbines using

Big Data frameworks. In 2017 IEEE international conference on prognostics and health management (ICPHM) (pp. 70-77). IEEE.

[12] Lei, X., Dong, Y., & Frangopol, D. M. (2023). Sustainable life-cycle maintenance policymaking for network-level deteriorating bridges with a convolutional autoencoder–structured reinforcement learning agent. Journal of Bridge Engineering, 28(9), 04023063.

[13] Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., & Sui, F. (2018). Digital twin-driven product design, manufacturing and service with big data. The International Journal of Advanced Manufacturing Technology, 94, 3563-3576.

[14] Zhu, J., Zhang, W., & Li, X. (2019). Fatigue damage assessment of orthotropic steel deck using dynamic Bayesian networks. International Journal of Fatigue, 118(1), 44-53.

[15] Zhu, J., Chen, Y., Heng, J., Wu, M., Zhang, Y., & Li, Y. (2024). Probabilistic corrosion-fatigue prognosis of rib-to-deck welded joints in coastal weathering steel bridges exposed to heavy traffic. International Journal of Fatigue, 182, 108210.

[16] Zhu, J., Zhang, W., & Li, X. (2019). Fatigue damage assessment of orthotropic steel deck using dynamic Bayesian networks. International Journal of Fatigue, 118(1), 44-53.

[17] Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. Journal of Manufacturing Systems, 48, 157-169.

[18] Keshmiry, A., Hassani, S., Mousavi, M., & Dackermann, U. (2023). Effects of Environmental and Operational Conditions on Structural Health Monitoring and Non-Destructive Testing: A Systematic Review. Buildings, 13(4), 918.

[19] Zhang, J., Heng, J., Dong, Y., Baniotopoulos, C., & Yang, Q. (2024). Coupling multi-physics models to corrosion fatigue prognosis of high-strength bolts in floating offshore wind turbine towers. Engineering Structures, 301, 117309.

[20] Heng, J., Zheng, K., Feng, X., Veljkovic, M., & Zhou, Z. (2022). Machine Learning-Assisted probabilistic fatigue evaluation of Rib-to-Deck joints in orthotropic steel decks. Engineering Structures, 265, 114496.

[21] Lai, L., Dong, Y., & Smyl, D. (2023). SHM-informed life-cycle intelligent maintenance of fatigue-sensitive detail using Bayesian forecasting and Markov decision process. Structural Health Monitoring, 14759217231160412.

[22] Zhang, Z., & Sun, C. (2021). Structural damage identification via physics-guided machine learning: a methodology integrating pattern recognition with finite element model updating. Structural Health Monitoring, 20(4), 1675-1688.

[23] Heng, J., Zheng, K., Kaewunruen, S., Zhu, J., & Baniotopoulos, C. (2019). Dynamic Bayesian network-based system-level evaluation on fatigue reliability of orthotropic steel decks. Engineering Failure Analysis, 105, 1212-1228.

[24] Lei, X., & Dong, Y. (2022). Deep reinforcement learning for optimal life-cycle management of deteriorating regional bridges using double-deep Q-networks. Smart Structures and Systems, 30(6), 571-582.
[25] Egorov, M. (2015). Deep reinforcement learning with pomdps. Tech. Rep. (Technical Report, Stanford University, 2015), Tech. Rep.
[26] Frangopol, D. M., Dong, Y., & Sabatino, S. (2019). Bridge life-cycle performance and cost: analysis, prediction, optimisation and decision-making. In Structures and Infrastructure Systems (pp. 66-84). Routledge.
[27] Rebelo, C. & Baniotopoulos, C. (2022). Modular Energy Islands for Sustainability and Resilience Proceedings CESARE'22, 6-9 May, 2022, Irbid.
[28] Zhang, Y., Zheng, K., Heng, J., & Zhu, J. (2019). Corrosion-fatigue evaluation of uncoated weathering steel bridges. Applied Sciences, 9(17), 3461.
[29] National Data Buoy Center (NDBC), 2022. https://www.ndbc.noaa.gov/obs.shtml
[30] National Renewable Energy Laboratory (NREL), 2022. OpenFAST – an open-source wind turbine simulation tool. https://github.com/openfast

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Figure 1 A typical framework of AI-boosted DT4ENG in wind turbines.

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

Figure 3 Backward DT to integrate model prediction, inspection results and monitoring data.

Figure 4 Engine for DT-informed decision making: (a) Dynamic POMDP; (b) Reinforcement learning with muti-agent.

Figure 5 Probabilistic deterioration assessment of FOWTs by forward DT.

Figure 6 Crack growth and failure modes of the most critical bolt in ring-flange connections.