doi: 10.5937/SimTerm24053S

Applications and Challenges of Digital Twins of Floating Wind Turbines

Maria-Styliani Daraki[a] , Beatrice Mina[b], Muhnad Almasoudi[c], Barbara Charalambidi[a], Marko Mančić[d], Junlin Heng[e], Charalampos Baniotopoulos[e]

[a] *School of Production Engineering and Management, Technical University of Crete, Chania, Greece, ISO 3166-2:GR, mdaraki1@tuc.gr, bcharalambidi@gmail.com*
[b] *University School for Advanced Studies IUSS Pavia, Pavia, Italy, IT, beatrice.mina@iusspavia.it*
[c] *School of Engineering, University of Birmingham, Birmingham, United Kingdom, GB, mxa1538@student.bham.ac.uk*
[d] *University of Nis, Faculty of Mechanical Engineering, Nis, Serbia, RS, marko.mancic@masfak.ni.ac.rs*
[e] *Department of Civil Engineering, University of Birmingham, Birmingham B15 2TT, United Kingdom, GB, ccbanio@gmail.com, h.junlin@bham.ac.uk*

Abstract: A digital twin is a virtual model of a physical asset, like a wind turbine, synchronized with real-time data to provide insights into its performance, condition, and behavior. This technology has applications in environmental perception, condition assessment, predictive maintenance, anomaly detection, and optimizing the operational parameters of floating offshore wind turbines. This paper reviews the current state of research and practical applications of digital twins in this field. It explores the concept, focusing on the challenges posed by climate, system dynamics, and structural issues in wind turbines. Case studies include topics such as Fatigue Limit State, pitch blade control, drivetrain performance, power output, and structural strain. Technical challenges in implementing digital twins include issues related to data collection, transfer, communication, and standardization, as well as the robustness of models in accurately simulating physical behaviors. Solutions can be found through AI, IoT, advanced simulation tools, and improved monitoring techniques. Non-technical challenges, typical for emerging technologies, are mainly tied to human factors. However, the benefits and financial advantages of digital twin technology are expected to promote its widespread adoption in industrial applications.

Keywords: Digital twins, Fatigue, Floating offshore wind turbine, Wind energy.

1. Introduction

The development of digital twins technology provides an innovative approach to the monitoring and maintenance of offshore wind turbines, offering a flexible universal solution for performance prediction and improvement, design, monitoring, maintenance, life time predictions, stain and fatigue predictions etc. A digital twin is a virtual representation of a physical asset, such as a wind turbine, that is synchronised with real-time data, enabling a comprehensive understanding of its performance, condition, and behaviour [1], [2]. The offshore wind power has emerged as a critical component of the global transition to renewable energy, with ambitious targets for capacity expansion planned to be met by offshore wind in 2050 [3]. This is estimated to equal 450 GW worldwide [1]. While fixed-bottom offshore wind turbines have seen significant advancements in recent years, the deployment of floating offshore wind turbines (FOWTs) is poised to be a game-changer, unlocking previously in a deep-water wind resources [4]. The development of digital twins for floating offshore wind turbines is a relatively new and rapidly evolving field, with a growing body of research and industry applications emerging. One of the key challenges in creating digital twins for floating offshore wind turbines is the complex, dynamic nature of the offshore environment, which includes factors such as wind, waves, currents, and seabed conditions [5]. To address these challenges, researchers and industry players have developed advanced modelling techniques that combine computational fluid dynamics, structural dynamics, and other physics-based models to accurately represent the behaviour of the floating turbine system [6].

These digital representations can be leveraged for a variety of purposes, including environmental perception, response measurement, condition assessment, predictive maintenance, anomaly detection, and optimization of operational parameters [1]. By combining real-time data with physics-based models, digital twins can provide a more complete picture of the turbine's performance, allowing for proactive intervention and informed decision-making [7]. Application of digital twins in offshore wind is the ability to create standalone, descriptive, and predictive models of the turbine and its operating environment [7]. Digital twins in the offshore wind industry offer the ability to simulate and test various scenarios before implementing them in the physical world [8]. This capability is particularly valuable in the context of reconfigurable manufacturing systems, where digital twins can be used to model and optimise the manufacturing process, ensuring that changes are thoroughly evaluated before implementation [8]. This allows for the modelling and optimization of the manufacturing process, ensuring that changes are thoroughly evaluated before implementation [9].

The goal of this work is to identify the challenges and opportunities associated with the development and application of digital twins for floating offshore wind turbines. The analysis and conclusions presented in the paper are based on the literature review. According to the literature review, digital twins provide many possibilities for academics, researchers and engineers, namely the estimation of aerodynamic loads [10], vibration analysis, anomaly detection and predictive maintenance [11] and prediction of power production [5].

2. The state of art of Digital Twins for floating wind turbines

Emerging technologies and challenges of Digital Twins in Wind Turbines are described in [1], where digital twins capabilities are ranked into categories from standalone to autonomous in five categories. In this review, the authors have identified the growing interest and need for digital twins, however in wind energy, digital twins are still in the early stage of implementation, with most of the applications focused on monitoring and diagnostics [1].

A digital twin typically consists of the following [12]:

– Physical System: This encompasses the actual wind turbine and its critical components, including the rotor, blades, shaft, generator, tower, and nacelle.
– Digital System: This system mirrors the physical system in a virtual environment, incorporating data storage, digital models, and mathematical modeling to simulate real-world behavior.
– Connection System: This system facilitates communication between the physical and digital twins, enabling data exchange through protocols like Modbus, OPC UA, MQTT, Ethernet/IP, and CANopen.
– Service System: This system leverages data from the DT to provide services like predictive maintenance, performance optimization, and fault diagnosis.

One more definition for the process of twinning in the Digital Twin (DT) approach is shown in Fig. 1, based on [13]. Essentially, data is collected from a specific physical asset (shown in orange) and used to update a related simulation model (or a simplified version of it, represented in green). The updated model is used to predict what might happen next, and those predictions help guide decisions to control the physical asset. The control system takes care of these actions automatically. This process of observing, updating, predicting, and acting keeps happening in real-time to adjust for any changes in the asset's behavior as time goes on.

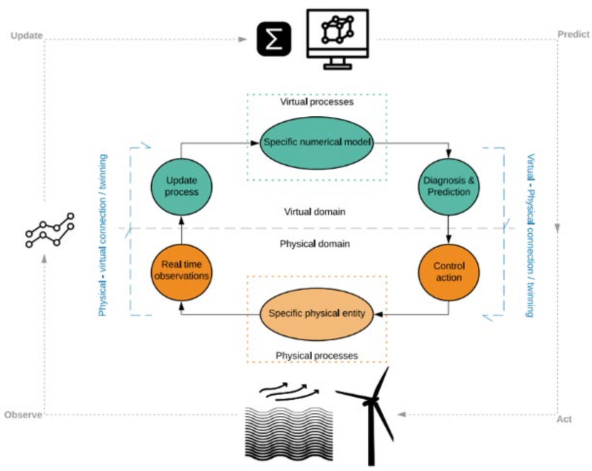

Figure 5. The process of twinning in the Digital Twin (DT) approach [13] (under CC BY 4.0).

Digital twin modelling was applied to predictive maintenance of gearboxes of offshore wind turbine drivetrains in [14], where complex dynamic behaviour of the drivetrain was analysed using multi degree of freedom torsional model, an algorithm was proposed to estimate rotor-generator torque and its dynamics, and the goal was predicting the estimated lifetime of the gearbox [14]. Digital twin modelling was analyzed in [12] for monitoring and fault diagnostics. Digital twin application for predictive maintenance of drivetrains was also applied in [15], where anomaly diagnostics were determined.

The key challenges of development of digital twins for wind turbines are [1]:

- Standard related – there is a lack of standardised data formats and communication protocols which present difficulties for exchange of information, applied models and systems between different users.
- Data related – there is a lack of high quality data from different sources during the wind turbine lifecycle, followed by challenges of managing, storing and processing of this data [1], [12].
- Model-related – there is a challenge to develop high quality accurate and reliable models that can faithfully represent the physical and dynamic behavior of wind turbines, and finally,
- Industrial acceptance – there is a challenge of adopting new technologies, where demonstrations of benefits and financial benefits may play a key role.

The application of Digital Twin technology to improve the fatigue analysis of offshore wind turbine structures is presented in [13], where real-time observation data is integrated with simulation models, a DT may provide a more accurate and reliable assessment of the structural integrity of these critical assets. Despite real time data, uncertainty in predicting the fatigue life of OWT structures is stated by the authors [13] and is presented in the Figure 2.

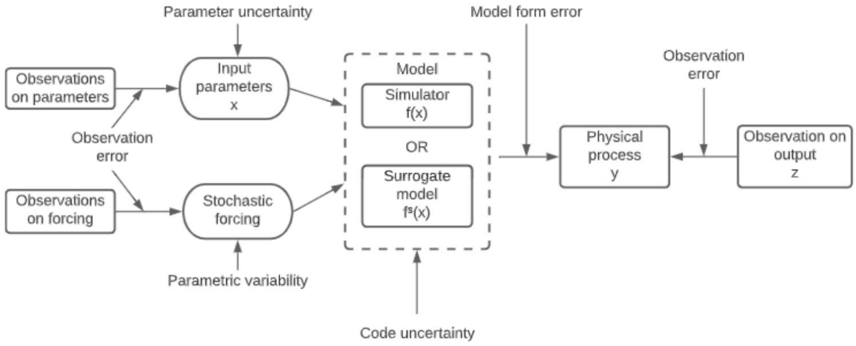

Figure 6. Sources of uncertainty relevant to the DT paradigm for some true physical process y, including those relevant to the observations z of the physical process, and those relevant to the model $f(x)$ (or it's surrogate $f\,s\,(x)$) of the physical process [13] *(under CC BY 4.0).*

3. Digital twins of Floating Offshore Wind Turbines

The wind turbine operation and maintenance can be improved through developing a Digital Twin (DT). The most common abilities of a DT are to monitor, analyse, and forecast the performance of the wind turbines by giving a digital representation of the physical system. The DT supports preventive maintenance through early indications of probable problems. Consequently, this may lead to increased productivity, minimised downtime, and better security [16]. From their study, it was observed that the DTs of wind turbines can have different connectivity options, namely supervisory control and data acquisition (SCADA), wireless sensor networks (WSN), smart grids (SG), Internet of Things (IoT), and cloud-based systems. There are multiple purposes for these connecting protocols within the DT other than facilitating real-time monitoring and control over wind turbines. For instance, information collected via data acquisition or other sensors could be utilised to predict when maintenance should be done in a wind turbine in order to avoid serious breakdowns [17]. This combination makes DT more efficient when integrating such communication methods and can enhance performance, reduce maintenance costs, and increase reliability in terms of the turbine. In some cases, creating a Digital Twin (DT) system requires the integration of many different sensors, controls, and software parts that work together to emulate the behavior of the actual wind turbine.

Moreover, Moghadam and Nejad [15] have laid a foundation for establishing preventive maintenance in FWT drivetrain systems by monitoring component residual lifetime by using DT and employing a stochastic physics-based model to estimate the remaining useful life (RUL) of drivetrain components. The research from [1] suggests that wind farms' efficiency can be improved across their life cycle starting with design [18] and siting [19], through construction [20] and operations [21], finishing with maintenance [22] and decommissioning [23], which are digitising. It is worth noting here that offshore wind farms are typically situated in remote hazardous environments where accessibility is challenging. Condition-based maintenance reduces the number of on-site maintenance tasks. Predictive maintenance helps prevent unscheduled equipment downtime as well as avoid catastrophic failures by reacting to small faults before they turn into big problems [22]. Therefore, the construction of a DT can provide an efficient solution. Regarding the infrastructures, the need for digital twins comes from the extreme loadings applied on energy-related infrastructure and the increased significance of fatigue effects. Digital twin technologies enable reliable models that could follow structures from their inception through their whole life cycles, making fatigue and degradation prediction more reliable and facilitating effective predictive maintenance schemes [24].

4. Identifying some problems related to weather, wind conditions on floating offshore wind turbines

According to [25] due to the harsh environment of the oceans, floating offshore wind turbines (FOWT) can be in danger especially if the wind speed increases more than the designed limit. As the authors mentioned, several issues can happen to the turbines such as mechanical temperature and physical temperature problems. In detail, mechanical problems can be described specifically in terms of potential high or low-temperature issues that result in failures in bearing. High temperature leads to a decrease in lubricant viscosity, fatigue, seals drying and cracking, and weakening retainer and cage. Low temperature causes raise the lubricant viscosity, skidding, and increasing torque. In addition, physical problems can be concluded in icing blades and moisture. Also, moisture can cause a reaction with metal parts that weaken and degrade mechanical elements. On the other hand, vibration is a critical issue that may stop or reduce the steady movement of the blades. The reasons behind this phenomenon are loading, flow of the sea water, wind speed, and rotation of the blades.

5. Potential digital twins' solutions for weather, wind conditions on floating offshore wind turbines

Digital twins can predict the issues before it happens and that can be through sensors and forecasting linked to the FOWT to insure the health and safety for this turbine [26]. In this work is detailed that the integration of the physical and digital engineering system is complicated, yet the applications of these combined technologies can prevent the failure of the turbine. According to [27], wind forecasting and wind data optimization can lead to prevent the collapse of offshore wind turbine (OWT) through Extreme Wind Period (EWP) that enable the turbines to shut down when the wind speed is more than 25 m/s and reoperate itself again when it becomes 20 m/s to achieve the best quality of the power optimization and to prevent any other issues.

Integrating more than one technology can lead to healthier wind turbines due to the multiple predictions of each possible problem. According to [28], three weather forecasting methods has been integrated; Markov Chains, gradient boosting, and hybrid progression/statistical method to use them as an input into the lifecycle of the wind turbine to enhance the performance of the energy production, availability, and revenue. In addition, it can predict the failure rate and the performance of the indicators. In [29] is investigated that Computational Fluid Dynamics (CFD) can be coupled with weather predictions, that can be based on Reynolds Averaged Navier Stokes (RANS) with mesoscale simulation to enhance the prediction of loads and energy output, the accuracy of the results of this coupled simulation compared with the open-source LiDAR that showed a relevant result. Many of the ideas can be applied in the floating offshore wind turbines, but the most important is the prediction of issue before it happens. That is what weather predictions and wind data optimization can do, preventing the mentioned problems above and many other problems that are not mentioned here, and that lead to extending the wind turbine health and safety.

6. Structural challenges of floating turbines and DT solutions

With respect to land-based wind turbines, floating offshore wind turbines (FOWT) undergo major loads and stability issues due to their interaction with the sea state. The aim, during the design stage, is to reduce platform motion in all the 6 degrees of freedom and in particular minimize pitch motion. Hence the natural frequencies of the platform oscillations need to be outside some critical regions corresponding to: the range of wave frequencies, the frequency at which the blade passes the tower and the third harmonic of such a frequency [25].

Another source of instability arises from the employment of the blade-pitch control techniques used for land-based turbines: when the wind speed is overrated, and thrust decreases, a negative damping develops, causing a large motion response [26], [27]. Hence control technique should be adapted to FOWT. Therefore, beyond the stability study in the designing phase, stability monitoring during the whole lifecycle of FOWTs has an important role in reducing and preventing failure risk.

Digital twin models come in handy for predicting the response of those structures, in terms of loads but also of power output, depending on the sea state. In [10] the implemented digital twin estimates the aerodynamic states and motions of the structure. It takes as input measured parameters like rotor speed, heave and pitch of the platform, and through a Kalman filter, which uses a linear wind turbine model (within WELIB toolkit), it predicts the desired states. Then those states are elaborated through a virtual sensing step to obtain the loads in the key points of the structure which give useful information to perform Operation and Maintenance (O&M) procedures.

Another implementation of digital twin technology is the prediction of the power output of wind turbines, this information indeed is crucial for the grid since the last one is susceptible to the variability and uncertainty of power supply. In [28] a physics-based output prediction model (P-bOPM) is developed for a 10 MW floating offshore wind turbine and is presented in the Figure 3. Within the physics-based model, instead of considering 6 degrees of freedom (dof) for the turbine motion, a reduced order model (ROM) that takes into account only 4 degrees of freedom (surge, heave, pitch, and yaw) is implemented. The ROM calculates in real time motion along the 4 dof of the floating body, receiving as input the marine environmental data and the blade pitch angle. Then the power output is calculated using the equation of the relative wind speed at the 4 dof and the real wind speed measured by an anemoscope. The ROM system is learned by Dynamic ROM Builder of ANSYS Twin Builder.

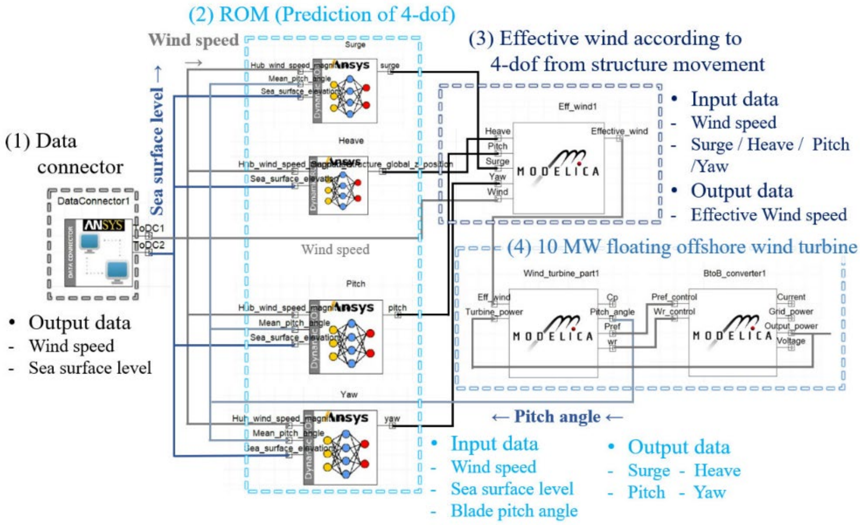

Figure 7. Configuration of the P-bOPM of a 10 MW FOWT model [28] (under open access Creative Common CC BY license).

Furthermore, essential components of FOWT are the mooring lines (MoLs); and their primary failure reasons are extreme loads and fatigue (both dependent on the axial tension). The usefulness of digital twins in this context can be two-fold [29]: on one hand they can predict the behaviour of a healthy mooring system and compare it with the actual one, and on the other they can forecast the real axial tension to enhance the MoLs' life span. The former kind of DT takes as inputs the instantaneous motion of the turbine and the sea state conditions, and outputs the healthy mooring lines axial tension, to be compared with the measured one. The latter instead, needs more input data: past and present motion, marine environment measurements and forecasted environmental conditions are required as well. To perform these analyses, Machine Learning algorithms are employed.

7. Real-scale applications and case study data review

Several sectors including manufacturing, healthcare, aviation, automotive transportation, infrastructure planning, and energy production have been using DTs in the recent past although they are not yet fully exploited and still face numerous challenges [30]. In particular, DTs are hardly used in wind power [31].

Among the others, there are findings in the literature that have implemented already real-scale applications and case studies. In the work of [13] is considered a further application of a DT paradigm to offshore wind turbine support structures for structural reliability under Fatigue Limit State (FLS) on bolted ring flange. In the research of [32], has been illustrated how a digital twin of the pitch angle controller was implemented on a TMS320F28379D Dual-Core Delfino™ Microcontroller device in Texas Instrument (TI). According to the hardware-in-loop (HIL) concept, a controller algorithm will be developed to diagnose the health condition of its behaviour on wind turbines. In the Figure 4, is described the design of the DT controller for the WT plant which has been done in two steps.

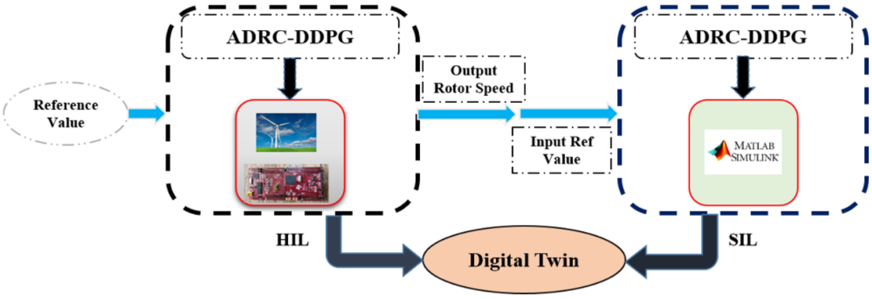

Figure 8. A proposed strategy for the combination of hardware-in-loop (HIL) and software-in-loop (SIL) testing [32] (under open access Creative Common CC BY license).

The paper of [15] uses a test case, which mainly proposes a residual life monitoring methodology for drivetrain components on floating offshore wind turbines. Specifically, in this work performance characteristics of the main shaft of the drivetrain system in DTU 10 MW wind turbine were simulated and tested for purposes of remaining useful life (RUL) estimation. Last but not least, in the terms of NorthWind industry project [1], two use cases are demonstrated of virtual reality. The first is referred to as onshore WT [5] and the second to offshore WT [7]. Based on [5] is visualized the DT of onshore WT and is detected in the Figure 5.

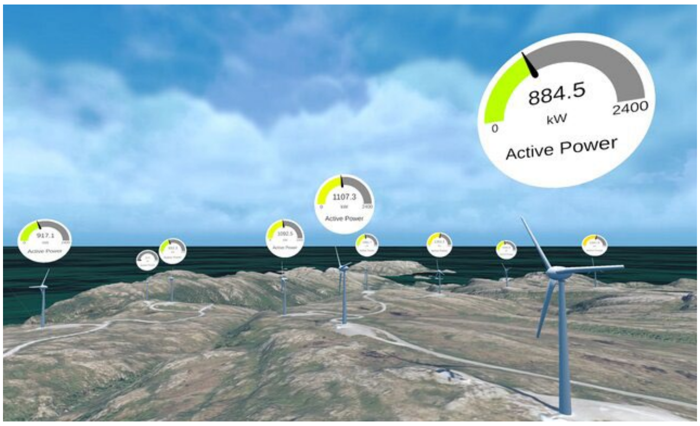

Figure 9. Descriptive digital twin with text and gauges showing active power of each turbine [5] (under CC BY 4.0).

Conclusions

The four main areas in which digital twins can be applied for the wind industry are condition monitoring, fault diagnosis, predictive maintenance, adaptive control and power output which can help it become an effective technology. Operators who are trying to monitor their wind turbine ID and other parts can create an accurate digital model of their systems and components, thus being able to carry out better asset management, detect problems, and diagnose the faults effectively and efficiently. The application of this technology is aimed at cutting down the cost of maintenance work, extending the life of wind turbines, and bringing up the efficiency level of wind turbines offshore through a monitoring system which provides real-time data and accurate information on the actual state of the system or subsystem. While there are still challenges for both development and wider applications of digital twins, the research paper showed that progress is being made in this field and with it, the industry will gain tangible advantages.

A more rapid development of digital twins may be expected in the near future. Furthermore, with the development of data handling techniques and standardization progress, integration of data, simulation behavioural models to converge leading to a single digital twin system for floating wind turbines, which would represent almost a "turn key" solution for prediction of behaviour of wind turbines, helping decision makers and stakeholders strengthen the position of floating wind turbines to the market even further.

References

[1] F. Stadtmann *et al.*, "Digital Twins in Wind Energy: Emerging Technologies and Industry-Informed Future Directions," *IEEE Access*, vol. 11, pp. 110762–110795, 2023, doi: 10.1109/ACCESS.2023.3321320.

[2] H. Van Der Valk, J. Hunker, M. Rabe, and B. Otto, "Digital Twins in Simulative Applications: A Taxonomy," in *2020 Winter Simulation Conference (WSC)*, Orlando, FL, USA: IEEE, Dec. 2020, pp. 2695–2706. doi: 10.1109/WSC48552.2020.9384051.

[3] G. Rinaldi, P. R. Thies, and L. Johanning, "Current Status and Future Trends in the Operation and Maintenance of Offshore Wind Turbines: A Review," *Energies*, vol. 14, no. 9, p. 2484, Apr. 2021, doi: 10.3390/en14092484.

[4] F. Li, L. Li, and Y. Peng, "Research on Digital Twin and Collaborative Cloud and Edge Computing Applied in Operations and Maintenance in Wind Turbines of Wind Power Farm," in *Advances in Transdisciplinary Engineering*, D. Dobrotă and C. Cheng, Eds., IOS Press, 2021. doi: 10.3233/ATDE210263.

[5] F. Stadtmann, A. Rasheed, and T. Rasmussen, "Standalone, Descriptive, and Predictive Digital Twin of an Onshore Wind Farm in Complex Terrain," *J. Phys.: Conf. Ser.*, vol. 2626, no. 1, p. 012030, Oct. 2023, doi: 10.1088/1742-6596/2626/1/012030.

[6] Jpt Staff, "Digital Twins Mature in the North Sea," *Journal of Petroleum Technology*, vol. 71, no. 12, pp. 41–43, Dec. 2019, doi: 10.2118/1219-0041-JPT.

[7] F. Stadtmann, H. A. G. Wassertheurer, and A. Rasheed, "Demonstration of a Standalone, Descriptive, and Predictive Digital Twin of a Floating Offshore Wind Turbine," in *Volume 8: Ocean Renewable Energy*, Melbourne, Australia: American Society of Mechanical Engineers, Jun. 2023, p. V008T09A039. doi: 10.1115/OMAE2023-103112.

[8] J. Kombaya Touckia, N. Hamani, and L. Kermad, "Digital twin framework for reconfigurable manufacturing systems (RMSs): design and simulation," *Int J Adv Manuf Technol*, vol. 120, no. 7–8, pp. 5431–5450, Jun. 2022, doi: 10.1007/s00170-022-09118-y.

[9] J. D. M. De Kooning, K. Stockman, J. De Maeyer, A. Jarquin-Laguna, and L. Vandevelde, "Digital Twins for Wind Energy Conversion Systems: A Literature Review of Potential Modelling Techniques Focused on Model Fidelity and Computational Load," *Processes*, vol. 9, no. 12, p. 2224, Dec. 2021, doi: 10.3390/pr9122224.

[10] E. Branlard, J. Jonkman, C. Brown, and J. Zhang, "A digital twin solution for floating offshore wind turbines validated using a full-scale prototype," *Wind Energ. Sci.*, vol. 9, no. 1, pp. 1–24, Jan. 2024, doi: 10.5194/wes-9-1-2024.

[11] O. O. Olatunji, P. A. Adedeji, N. Madushele, and T.-C. Jen, "Overview of Digital Twin Technology in Wind Turbine Fault Diagnosis and Condition Monitoring," in *2021 IEEE 12th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT)*, Cape Town, South Africa: IEEE, May 2021, pp. 201–207. doi: 10.1109/ICMIMT52186.2021.9476186.

[12] M. Wadhwani, S. Deshmukh, and H. S. Dhiman, "Digital Twin Framework for Time to Failure Forecasting of Wind Turbine Gearbox: A Concept," 2022, *arXiv*. doi: 10.48550/ARXIV.2205.03513.

[13] F. K. Moghadam, G. F. D. S. Rebouças, and A. R. Nejad, "Digital twin modeling for predictive maintenance of gearboxes in floating offshore wind turbine drivetrains," *Forsch Ingenieurwes*, vol. 85, no. 2, pp. 273–286, Jun. 2021, doi: 10.1007/s10010-021-00468-9.

[14] F. K. Moghadam and A. R. Nejad, "Online condition monitoring of floating wind turbines drivetrain by means of digital twin," *Mechanical Systems and Signal Processing*, vol. 162, p. 108087, Jan. 2022, doi: 10.1016/j.ymssp.2021.108087.

[15] J. Jorgensen, M. Hodkiewicz, E. Cripps, and G. M. Hassan, "Requirements for the application of the Digital Twin Paradigm to offshore wind turbine structures for uncertain fatigue analysis," *Computers in Industry*, vol. 145, p. 103806, Feb. 2023, doi: 10.1016/j.compind.2022.103806.

[16] M. Mahmoud, C. Semeraro, M. A. Abdelkareem, and A. G. Olabi, "Designing and prototyping the architecture of a digital twin for wind turbine," *International Journal of Thermofluids*, vol. 22, p. 100622, May 2024, doi: 10.1016/j.ijft.2024.100622.

[17] U. Singh and M. Rizwan, "SCADA system dataset exploration and machine learning based forecast for wind turbines," *Results in Engineering*, vol. 16, p. 100640, Dec. 2022, doi: 10.1016/j.rineng.2022.100640.

[18] T. Ashuri, M. B. Zaaijer, J. R. R. A. Martins, and J. Zhang, "Multidisciplinary design optimization of large wind turbines—Technical, economic, and design challenges," *Energy Conversion and Management*, vol. 123, pp. 56–70, Sep. 2016, doi: 10.1016/j.enconman.2016.06.004.

[19] R. Velo, P. López, and F. Maseda, "Wind speed estimation using multilayer perceptron," *Energy Conversion and Management*, vol. 81, pp. 1–9, May 2014, doi: 10.1016/j.enconman.2014.02.017.

[20] M. Asgarpour, "Assembly, transportation, installation and commissioning of offshore wind farms," in *Offshore Wind Farms*, Elsevier, 2016, pp. 527–541. doi: 10.1016/B978-0-08-100779-2.00017-9.

[21] V. R. Padullaparthi, S. Nagarathinam, A. Vasan, V. Menon, and D. Sudarsanam, "FALCON- FArm Level CONtrol for wind turbines using multi-agent deep reinforcement learning," *Renewable Energy*, vol. 181, pp. 445–456, Jan. 2022, doi: 10.1016/j.renene.2021.09.023.

[22] A. N. Nichenametla, S. Nandipati, and A. L. Waghmare, “Optimizing life cycle cost of wind turbine blades using predictive analytics in effective maintenance planning,” in *2017 Annual Reliability and Maintainability Symposium (RAMS)*, Orlando, FL, USA: IEEE, 2017, pp. 1–6. doi: 10.1109/RAM.2017.7889682.
[23] C. A. Irawan, G. Wall, and D. Jones, “An optimisation model for scheduling the decommissioning of an offshore wind farm,” *OR Spectrum*, vol. 41, no. 2, pp. 513–548, Jun. 2019, doi: 10.1007/s00291-019-00546-z.
[24] G. E. Stavroulakis, B. G. Charalambidi, and P. Koutsianitis, “Review of Computational Mechanics, Optimization, and Machine Learning Tools for Digital Twins Applied to Infrastructures,” *Applied Sciences*, vol. 12, no. 23, p. 11997, Nov. 2022, doi: 10.3390/app122311997.
[25] A. Haghshenas, A. Hasan, O. Osen, and E. T. Mikalsen, “Predictive digital twin for offshore wind farms,” *Energy Inform*, vol. 6, no. 1, p. 1, Jan. 2023, doi: 10.1186/s42162-023-00257-4.
[26] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, “Shaping the digital twin for design and production engineering,” *CIRP Annals*, vol. 66, no. 1, pp. 141–144, 2017, doi: 10.1016/j.cirp.2017.04.040.
[27] N. A. Cutululis, N. K. Detlefsen, and P. E. Sørensen, “Offshore Wind Power Prediction in Critical Weather Conditions: 10th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Farms,” *Proceedings*, 2011.
[28] A. Kolios, M. Richmond, S. Koukoura, and B. Yeter, “Effect of weather forecast uncertainty on offshore wind farm availability assessment,” *Ocean Engineering*, vol. 285, p. 115265, Oct. 2023, doi: 10.1016/j.oceaneng.2023.115265.
[29] A. Castorrini, S. Gentile, E. Geraldi, and A. Bonfiglioli, “Investigations on offshore wind turbine inflow modelling using numerical weather prediction coupled with local-scale computational fluid dynamics,” *Renewable and Sustainable Energy Reviews*, vol. 171, p. 113008, Jan. 2023, doi: 10.1016/j.rser.2022.113008.
[30] E. C. Edwards, A. Holcombe, S. Brown, E. Ransley, M. Hann, and D. Greaves, “Evolution of floating offshore wind platforms: A review of at-sea devices,” *Renewable and Sustainable Energy Reviews*, vol. 183, p. 113416, Sep. 2023, doi: 10.1016/j.rser.2023.113416.
[31] J. Jonkman, “Influence of Control on the Pitch Damping of a Floating Wind Turbine,” in *46th AIAA Aerospace Sciences Meeting and Exhibit*, Reno, Nevada: American Institute of Aeronautics and Astronautics, Jan. 2008. doi: 10.2514/6.2008-1306.
[32] T. J. Larsen and T. D. Hanson, “A method to avoid negative damped low frequent tower vibrations for a floating, pitch controlled wind turbine,” *J. Phys.: Conf. Ser.*, vol. 75, p. 012073, Jul. 2007, doi: 10.1088/1742-6596/75/1/012073.
[33] C. Kim *et al.*, “Design, Implementation, and Evaluation of an Output Prediction Model of the 10 MW Floating Offshore Wind Turbine for a Digital Twin,” *Energies*, vol. 15, no. 17, p. 6329, Aug. 2022, doi: 10.3390/en15176329.
[34] J. Walker, A. Coraddu, M. Collu, and L. Oneto, “Digital twins of the mooring line tension for floating offshore wind turbines to improve monitoring, lifespan, and safety,” *J. Ocean Eng. Mar. Energy*, vol. 8, no. 1, pp. 1–16, Feb. 2022, doi: 10.1007/s40722-021-00213-y.
[35] F. Tao and Q. Qi, “Make more digital twins,” *Nature*, vol. 573, no. 7775, pp. 490–491, Sep. 2019, doi: 10.1038/d41586-019-02849-1.
[36] A. Ciuriuc, J. I. Rapha, R. Guanche, and J. L. Domínguez-García, “Digital tools for floating offshore wind turbines (FOWT): A state of the art,” *Energy Reports*, vol. 8, pp. 1207–1228, Nov. 2022, doi: 10.1016/j.egyr.2021.12.034.
[37] A. Parvaresh, S. Abrazeh, S.-R. Mohseni, M. J. Zeitouni, M. Gheisarnejad, and M.-H. Khooban, “A Novel Deep Learning Backstepping Controller-Based Digital Twins Technology for Pitch Angle Control of Variable Speed Wind Turbine,” *Designs*, vol. 4, no. 2, p. 15, Jun. 2020, doi: 10.3390/designs4020015.