

Towards an Integrative Framework for Digital Twins in Wind Power

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Abstract - The present global climate crisis necessitates urgent integration of sustainable and renewable energy resources, coupled with digital technology. Renewable energy stands out as a viable solution, and among the various renewable energy sources, wind power is believed to play a crucial role in this transition. In the era of industrial digitalization, implementing smart monitoring and operation becomes a vital step toward optimizing resource utilization. Consequently, the application of Digital Twins (DT) emerges as a promising approach to enhance power output in the wind energy sector. DTs for energy systems encompass multiple areas of study, such as smart monitoring, big data technology, and advanced physical modeling. While several frameworks exist for structuring DTs, few standardized methods have been established based on the experience gained. To address this gap, the present research proposes an integrative development framework for DTs, tailored explicitly to the aerodynamics of wind turbines, to ensure their successful operation throughout the entire lifecycle, from aggregation to performing actions. A seven-step framework is presented, which identifies the potential components and methods required to create a fully developed DT.

Keywords - DT, Wind Turbine, Renewable Energy, Artificial Intelligence

I. INTRODUCTION

Climate change poses a substantial risk to the existence of life on our planet, and the need for swift action is imperative [1]. The shift towards a low-carbon society is a persistent undertaking, and renewable energy is playing a vital role in advancing this goal. In contrast to non-renewable energy, which is obtained from finite energy reservoirs, renewable energy is extracted from sustainable energy sources, with wind power being a notable example. [2]. The Mitigation Climate Change report by the IPCC highlights wind and solar energy as the most promising technologies for cost-effective reduction of greenhouse gas emissions.

The rise of digitalization and the transition to digital technology underscore the need for the advancement of Digital Twin (DT) technology across mechanical systems. This innovative approach demands cooperation among diverse stakeholders, including both industry and academia. In a comprehensive examination of Digital Twins in the wind energy sector. [3], the authors recommend that academia and research institutes contribute to developing virtual and predictive twins accessible to society through open-source software. Similarly, collaboration is encouraged in building machine learning models using open-source software,

citing the Python programming language as an example of how a large community can enhance a tool through additional features and bug fixes after its initial release. Developing a fully capable DT with high-fidelity modeling can be time-consuming due to its complexity [4] and [5]. However, utilizing open-source resources and frameworks for DTs can significantly reduce development time compared to each firm creating its proprietary DT from scratch. Thus, it is advantageous to leverage technology accessible to all interested parties.

Identifying precise definitions for Industry 4.0 and Digital Twins (DT) across various application domains is a complex task. Diverse criteria and expectations govern what capabilities a digital model must possess to be considered a DT. These often include real-time data interchange between physical and digital system components and the capacity to analyze and leverage this data for optimizing both the digital and physical systems. Frequently, various terms are employed to describe distinct types of digital models. Therefore, this study presents an integrative framework for DT implementation in wind turbines, providing a systematic approach for developing DT models specifically designed for these systems. Each stage in the model construction process is meticulously described using schematics, ensuring a comprehensive understanding of the effective method for constructing these models.

II. DIGITAL TWIN CONCEPT

We introduce the diverse definitions of DT and associated concepts in the literature regarding model digitization. We elucidate the specific meaning attributed to each definition and explore their interpretations across different levels. This comprehensive comprehension will serve as a foundation for developing an integrative model for DTs. The categorization of Digital Twins (DT) can be based on their specific application area and the manner in which data is exchanged between the physical system and its virtual counterpart. In terms of application area, various types of DTs exist [6]:

1. Digital Twin Prototype (DTP): A DTP encompasses datasets like 3D models, Bills of Materials, Bills of Processes, and other essential information needed to describe and create a physical replica that mirrors the virtual version.
2. Digital Twin Instance (DTI): A DT that faithfully represents a physical asset throughout its entire life cycle, connected to the real-world asset through a

continuous digital thread that includes historical data, real-time sensor data, tests, and inspections.

3. **Digital Twin Aggregate (DTA):** An aggregation of all DTIs related to a particular system or a system of interconnected systems.
4. **Digital Twin Environment:** This term refers to a fully integrated, multidisciplinary application space where a DT operates for predictive purposes (estimating future behavior) or interrogative purposes (understanding historical or current states).
5. Fig. 1. shows the DT classification based on data flow and the various classes are described below.
1. **Digital Model:** The digital model is defined as a virtual representation of a physical asset that accurately describes its predetermined set of behaviors. The digital model does not exchange data automatically with its physical counterpart, and new information must be manually added [7].

2.

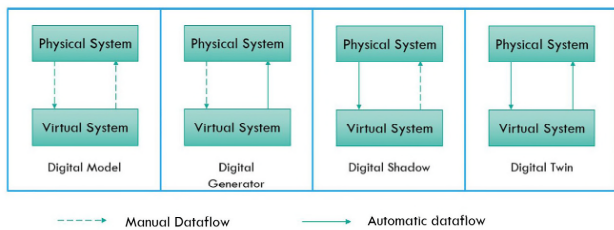


Fig. 1. Different concepts related to Digital Twin [8]

3. **Digital Shadow:** A digital shadow is defined as providing an accurate depiction of a physical asset or process by automatically receiving near-real-time data from the physical system. It possesses the capability to evaluate data from a comprehensive database.
4. **Digital Generator:** It differs from the digital shadow in the sense that the flow of information from the virtual to the physical space is automatic, while from the physical world to the virtual the information has to be manually fed.
5. **Digital twin (DT):** In [3], a consensus definition of a DT is presented based on input from various authors and industrial partners. It is described as *a virtual representation of a physical asset or process*. However, in [4], the physical space is included in the DT, incorporating key features such as data acquisition, pre-processing, and actuators.

Besides these 4 classes, two more classifications are found in some of the literature.

6. **Digital Sibling:** The term digital sibling is used when discussing risk assessment and "what-if" analysis. In [9], it is defined as the offline mode of the DT used for conducting scenario analysis [3].

Digital Twin capability levels for wind energy

Wind turbines are considered cyber-physical systems (CPS), incorporating both physical components (e.g., blades, tower, nacelle, generator) and digital elements (such as control systems). When creating a Digital Twin (DT) for a CPS, the physical components are represented

through a digital model, while the digital elements can be directly integrated into the DT. This integrated DT serves as a tool for modeling, simulating, and optimizing the CPS. Throughout the entire lifecycle of the system, DTs find utility. For instance, during the design phase, they facilitate virtual testing, while in the manufacturing phase, they can simulate the production processes.

However, the most significant advantages of DTs become evident during the operational phase. They enable a continuous assessment of the historical, current, and future health of the system or asset. This information is valuable for devising inspection and maintenance plans. Moreover, DTs empower analysts to conduct intricate and safety-critical simulations, assessing dynamic risks before they manifest in reality. Operators can then make informed decisions to mitigate these dynamic risks, ensuring that risk and safety levels comply with industry regulations. [8]

Ensuring acceptable quality requires both the DT results and the developer's capabilities. The requirements for the DT encompass several aspects, including the quality of data, computation models, presentation of results in the user interface, and the functionality of the DT throughout its lifetime. [10] provides the functional elements in a DT's capability into six distinct levels, ranging from 0 to 5. These levels are described herein and are associated with the potential capabilities of a wind turbine's DT [11].

Standalone (0): This level involves describing the physical system without real-time data connectivity. It includes data modeling for contextualization and structure, providing a preview of the wind turbine and its surroundings before installation. It also allows for the simulation of the turbine in a local environment, considering various locations, heights, and weather data.

Descriptive (1): At this level, the DT utilizes real-time sensor data and historical data to describe the current state of the physical system. It notifies the user of events and provides live and historical sensor data on variables such as velocity, pressure, temperature, vibration, power generation, and humidity/density. The turbine's real-time representation includes notifications for critical conditions or changes.

Diagnostic (2): The DT supports condition monitoring and troubleshooting through diagnostic information. It provides indicators that offer vital information about the turbine's condition without requiring physical inspection. Remote inspection of turbine faults is also possible at this level.

Predictive (3): This level involves predicting future states or performance and supporting prognostic capabilities. The DT can predict wind conditions, and power generation, and estimate the remaining time until component failure.

Prescriptive (4): The prescriptive level goes beyond prediction and provides recommendations based on "what if" scenarios, risk analysis, and uncertainty quantification. It offers recommendations on, for example, when to start the turbine or carry out maintenance activities.

Autonomous (5): At the highest level, the DT operates as a closed control loop, replacing the user in decision-making and executive control actions on the system. This level includes power optimization through a control loop with a Maximum PowerPoint Tracker.

III. PROPOSED FRAMEWORK

This section provides an integrative framework developing a DT based on the high-order framework shown in Figure 2. The essential steps that are outlined are *Create*, *Communicate*, *Aggregate*, *Analyze*, *Insight*, and *Act*.

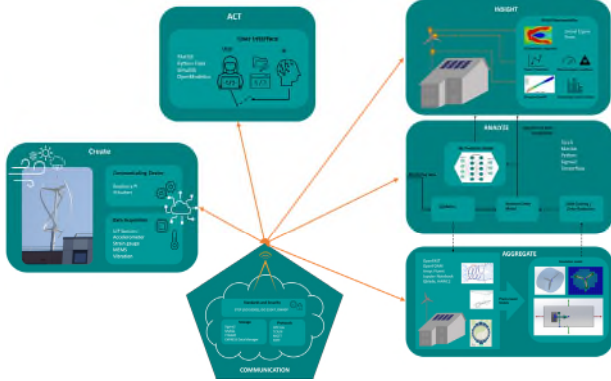


Fig. 2. DT development framework with the steps from Create to Act.

Create: The creation step encompasses a dual significance. On one hand, in the physical domain, it entails the installation of numerous sensors on the actual asset. On the other hand, in the digital realm, it involves the development of Computer-Aided Design (CAD) models that faithfully replicate the entire structure. Thus, the initial phase of designing the Digital Twin (DT) entails generating a standalone CAD model of the physical asset, such as a wind turbine, without any connectivity. Subsequently, functionalities and connections are incrementally incorporated until the DT reaches an acceptable capability level for its specific application. At this stage, the model does not need to be highly accurate since it does not provide real-time predictions and does not play a critical role in the future operation of the wind turbine. The precise prediction of aerodynamic performance for a wind turbine using an unconnected virtual model (Standalone DT) may not be achievable, but it does offer other benefits to the user (see Figure 3).

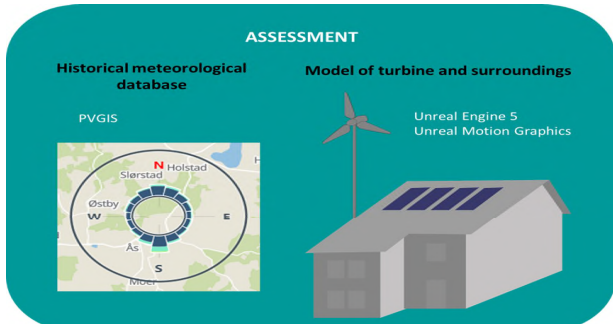


Fig. 3. In the assessment step, an unconnected virtual model with optional fidelity is made based on resource and site assessments.

Aerodynamic monitoring involves the placement of sensors for data acquisition, which includes wind speed, wind direction, and meteorological data like air temperature, humidity, and pressure. These parameters can be measured using anemometers, wind vanes, and temperature, humidity, and pressure sensors on the nacelle. Additionally, temperature and humidity sensors can aid in identifying ice formation, and if feasible, sensors can be installed on the turbine blades. Li-DAR technology can offer insights into upwind conditions, such as wind speed, to assist in controlling the mechanical system, such as an active yaw system.

Structural monitoring is accomplished through the use of accelerometers, strain gauges, vibration sensors, and Micro-Electro-Mechanical sensors (MEMS) placed on both the support structure and the blades. Among these, accelerometers are considered a promising technology for remote sensing. Further details regarding the design and implementation of structural monitoring in offshore wind farms are available in [12], which encompasses various accelerometers, both wired and wireless. Therefore, selecting the appropriate sensor technology for the specific wind turbine and its location (blade or structure) is of paramount importance.

In the **communication system**, the physical system is established, and sensor data can be transmitted using wireless communication technology for either temporary or long-term storage. Various communication protocols can be employed to facilitate effective communication between the system's components. These protocols serve as tools to enable seamless and efficient data exchange between the supervising entity, whether it's a human or an AI algorithm.

The primary objective of the Digital Twin (DT) is to **aggregate models** for the aerodynamic performance of a particular wind turbine at a specific location with a high degree of precision. This is accomplished by integrating empirical physical equations, numerical simulations, and experimental flow characteristics into a comprehensive multiscale model. The goal of this aggregation is to create a robust and dependable representation of the wind turbine's aerodynamic behavior, accounting for various factors and variables at different scales.

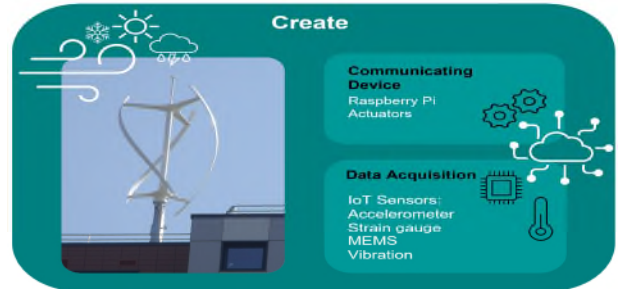


Fig. 4. The create step consists of physical sensors, data acquisition hardware and CAD models.



Fig. 5. The tools applied in the communication step allow data transferring between the physical and digital-physical systems.

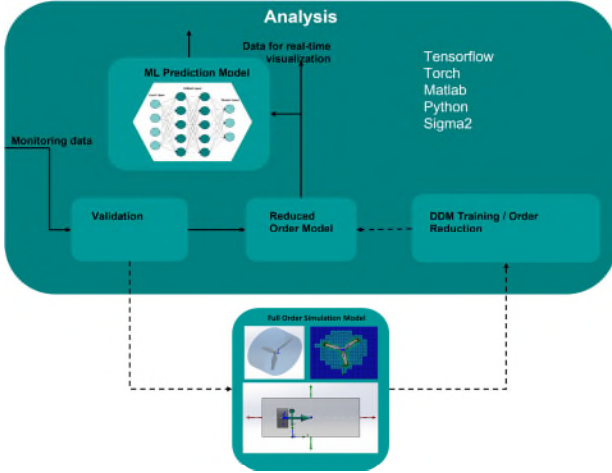


Fig. 6. Schematics of an analysis stage in DT.

The quality of monitoring and simulation data should be verified through an analysis process, which can involve methods like Blade Element Momentum (BEM), Reynolds-Averaged Navier-Stokes (RANS) [13], and Large Eddy Simulation (LES) [14]. This analysis step holds equal importance to the choice of the modeling technique in the previous phase, as it significantly influences the accuracy of the real-time virtual model. Additionally, aside from post-processing simulation outcomes, Data-Driven Modeling (DDM), including machine learning (ML), can be utilized to emulate physical relationships either in full or in part. This methodology is known as Hybrid Analysis and Modeling (HAM). By employing DDM and ML techniques, data-driven insights can be incorporated into the modeling process, ultimately enhancing the precision and dependability of the virtual model [15].

Insight: After fully updating the virtual model with the latest information, the simulation and analysis results can be seamlessly integrated into the selected platform during the assessment phase (as shown in Figure 8). Although there is limited literature discussing the specifics of virtualizing analysis results, it's likely because many analysis software tools already encompass this functionality.

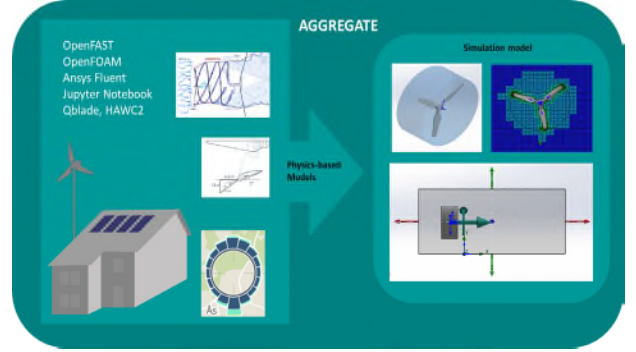


Fig. 7. The aggregate showing connection of virtual and real world.

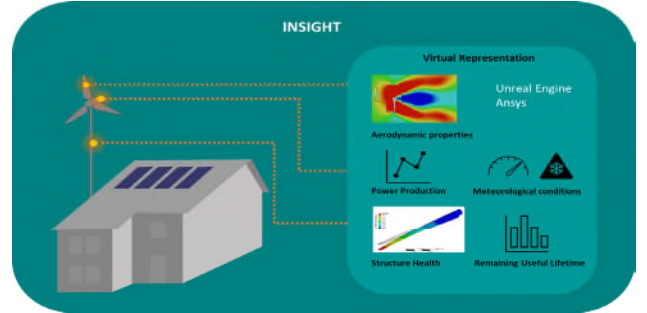


Fig. 8. Visualization of the physical system.

Act: By making use of the visualization tools offered by the insight platform, individuals can access valuable information to inform their decision-making and effectively strategize for future actions using predictive or prescriptive decision trees. This allows users to engage with the system's status via an intuitive interface. In order to create a self-governing decision tree, an additional overseeing entity, such as artificial intelligence (AI), becomes necessary to complete the control loop through model-driven decision-making. As depicted in Figure 9, it becomes feasible for the human user to disconnect the AI as a supervisor and directly act on the insights obtained from the analysis. This control loop can be easily implemented and executed using software like OpenModelica or Python Flask.

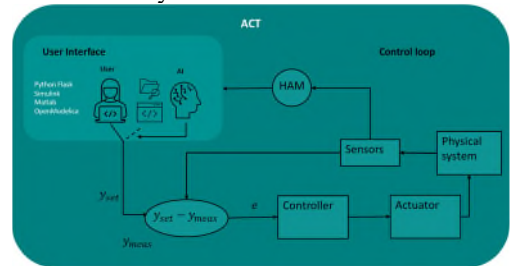


Fig. 9. Conceptual model of control loop of autonomous DT.

IV. CONCLUSION

In conclusion, this study highlights the potential of digital twins (DTs) as a promising approach to enhancing power output in the wind energy sector. The research aimed to create a conceptual development framework for DTs. The proposed seven-step framework, including Assessment, Create, Communicate, Aggregate, Analyze, Insight, and Act, provides a comprehensive guide for the

development of DTs in the wind power domain. The steps are summarized as herein. Create: In this step, the physical system is established, and data acquisition through IoT sensors is implemented. The data collected during this stage will serve as the foundation for subsequent steps. Communicate: The data acquired in the create step is then communicated and stored securely. This involves implementing a security system to protect the DT, defining protocols for data exchange and semantics, and ensuring accessible storage for the collected data. Aggregate: The Aggregate step involves utilizing models and computational software to simulate the behavior of the wind turbine and its surrounding environment. This requires input data from the Create step and high-fidelity modeling for aspects such as aerodynamic performance, power generation, and structural loads. Analyze: Once the simulation models are developed in the Aggregate step, the Analyze step focuses on data validation, model validation, and data-driven modeling. The collected data is validated for quality, and simulation models are validated for accuracy. Data-driven modeling techniques, such as machine learning and neural networks, can be employed to enhance the simulation results. Insight: The Insight step involves creating a real-time virtual model and visualizing technical data, predictions, and scenarios. The virtual model is updated with real-time information, allowing users to observe and analyze various parameters and scenarios using visualization tools like game engines. Act: The final step, Act, is enabled by a user interface that provides access to data, models, and insights generated in the previous steps. Through the user interface, users can perform actions on the physical wind turbine system using the communication and actuators within the DT.

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