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 from developing them. To address this gap, the present research aims to propose an integrative development framework for DTs, specifically tailored 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 for the creation of a fully developed DT. The steps explored in the present work range from *Assessment, Create, Communicate, Aggregate, Analyze, Insight, and Act* steps needed for the full realization of DTs.**

Keywords – **DT, Wind Turbine, Renewable Energy, Artificial Intelligence**

I. INTRODUCTION

Climate change presents a significant threat to life on Earth, and the urgency for immediate action is crucial [1]. The transition to a low-carbon society is a long-term endeavor, with renewable energy emerging as a key contributor towards this objective. Unlike non-renewable energy derived from static energy stores, renewable energy is harnessed from renewable sources of energy flows, with the wind being a prominent category [2]. The IPCC's Mitigation Climate Change report identifies wind and solar energy as the technologies with the highest potential to reduce greenhouse gas emissions at the lowest cost.

The recent emergence of digitalization and the shift towards digital technology necessitates the development of DT technology across all aspects of mechanical systems. This new paradigm requires collaborative efforts from various stakeholders, including industry and academia. In a review of DTs in the wind energy sector [3], the authors recommend that academia and research institutes contribute to the development of 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 a time-consuming process due to its complexity [4][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 that is accessible to all interested parties.

Established definitions related to Industry 4.0 and DT are hard to identify as many fields as possible of applications that exist. There exist different requirements and expectations of what a digital model should be capable of, before being classified as DT. Common criteria are real-time data exchange between the physical and digital system components and the ability to analyze and use the data to optimize the digital and physical systems. Some terms are often used to define the different instances 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 begin by introducing the diverse definitions of DT and associated concepts found 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 concept of DT can be classified based upon its application area and also on how the dataflow occurs between physical system and its virtual representation [cite my DT PAPER HERE]. Based on the application area the different types of DTs are [6]:

1. Digital Twin Prototype (DTP): A DTP consists of the informational sets (such as 3D models, Bills of Materials, Bills of Processes, etc.) which is imperative for describing and producing a physical version that emulates the virtual version.

2. Digital Twin Instance (DTI): A DT that represents its physical counterpart throughout its life cycle and is linked to a particular physical asset with the help of continuous digital thread (historical data, live data from sensors, tests and inspection).
3. Digital Twin Aggregate (DTA): An aggregation of all the DTIs, of a particular system or system of systems.
4. Digital Twin Environment: It refers to fully integrated, multidisciplinary physics application space for operating a DT for predictive (to estimate the future behavior) or interrogative (to understand the historical or current state) purposes.

Figure. 1. shows the DT classification on the basis of 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.

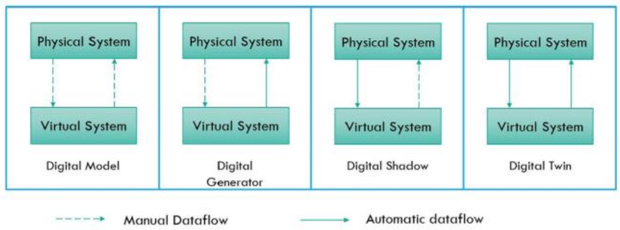


Fig. 1. Different concepts related to Digital Twin [8]

3. **Digital Shadow:** A digital shadow is defined to provide 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 digital shadow in the sense that the flow of information from the virtual to the physical space is automatic, while from physical world to 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 enabled through data and simulators for real-time prediction, optimization, monitoring, control, and informed decision-making*. The phrasing of this definition suggests that the physical asset is not a part of the DT system. 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 classification 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 offline mode of the DT used for conducting scenario analysis**.**
7. **Digital Thread:** The digital thread pertains to the product information gathered by the DT throughout the product's lifecycle, which is connected to Product Lifecycle Management (PLM). The digital thread can be utilized in the development of the product's next generation, holding information about the performance and design of the physical asset [3].

Digital Twin capability levels for wind energy

Wind Turbines are cyber-physical systems (CPS), meaning that they consist of both the physical/ hardware elements (such as Blades, tower, Nacelle, generator) and cyber/ software elements (such as control system, etc.). While building a DT of a CPS, the physical elements are represented by a digital model, while the cyber elements, can be included directly in the DT, which can then be used for modeling, simulating, and optimizing the CPS. The DTs can be used during entire life cycle of the system, for example during design phase they can be used for virtual testing, while during manufacturing they can simulate the production process. However, it is during the operational phase, that DT offers the maximum benefit as it can be utilized to continuously reflect the past, present and future health of the system/asset, which in turn can be used to formulate inspection and maintenance plans. Besides this, DTs also allow analyst to perform complex and safety critical simulations, in order to calculate the dynamic risk, before such an event happens in real life. The operators can then take necessary decisions in order to mitigate the dynamic risk estimated by the DT, and thus maintain risk and safety at the industry regulated levels. [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*.

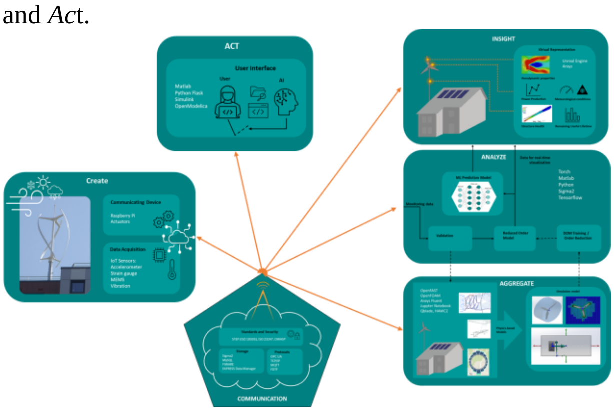


Fig. 2. DT development framework with the steps from Create to Act.

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).

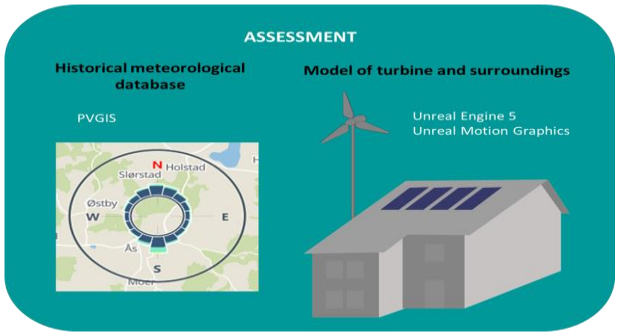


Fig. 3. In the assessment step, an unconnected virtual model with optional fidelity is made based on resource and site assessments.

For aerodynamic monitoring the sensors that can be placed for the data acquisition can be of wind speed, direction, and meteorological data such as air temperature, humidity, and pressure is necessary. These values can be measured from the nacelle using anemometers, wind vanes, and temperature, humidity, and pressure sensors. Additionally, temperature and humidity sensors can help detect ice formation, and if feasible, sensors can be placed on the blades. Li-DAR technology can be used to obtain insight into upwind conditions, such as wind speed, to support the control of the mechanical system (e.g., active yaw system) Structural monitoring can be achieved using accelerometers, strain gauges, vibration sensors, and Micro-Electro-Mechanical sensors (MEMS) mounted on both the support structure and blades Accelerometers are considered one of the most promising approaches for remote sensing technologies. The design and implementation of structural monitoring in an offshore wind farm are presented in [12], which includes the use of various accelerometers, both wired and wireless. Hence, finding suitable sensor technology for the specific wind turbine and location (blade or structure) is crucial.

Communication: In the communication system the physical system is created, sensor data can be transmitted using wireless communication technology for temporary or long-term storage. Communication between the system's components can utilize various protocols. Communication protocols serve as tools that enable the supervising entity (whether it be a human or an AI algorithm) to effectively communicate with the IoT sensors. Both communication and data representation protocols are necessary for seamless and efficient data exchange (see Figure 5).

Aggerate and Analyze: The main objective of the DT is to aggregate models for the aerodynamic performance of a specific wind turbine within a particular location with a high level of accuracy. This is achieved by combining empirical physical equations, numerical simulations, and experimental flow characteristics into a comprehensive multiscale model (see Figure 6, 7). The purpose of this aggregation is to create a robust and reliable representation of the wind turbine's aerodynamic behavior, considering various factors and variables at different scales.

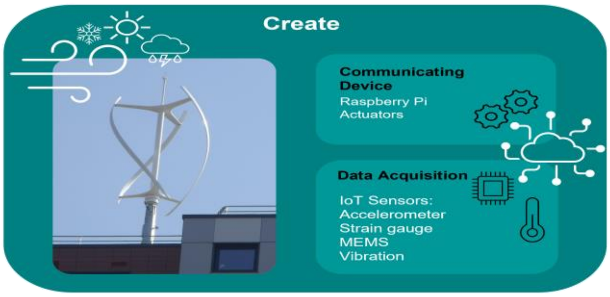


Fig. 4. The create step consists of physical sensors, data acquisition hardware and CAD models.

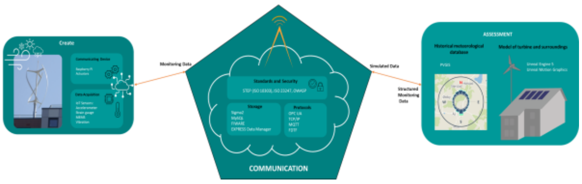


Fig. 5. The tools applied in the communication step allow data transferring between the physical and digital-physical systems.

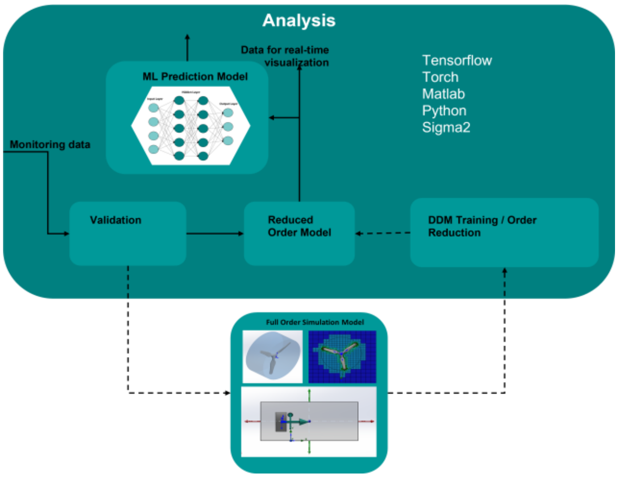


Fig. 6. Schematics of an analysis stage in DT. The dotted lines represent data transfer in the time-demanding numerical simulation using Full Order Models, and the solid lines show the real-time simulation loop.

Analysis should be conducted to validate the quality of the monitoring and simulation data, utilizing methods such as Blade Element Momentum (BEM), Reynolds-Averaged Navier-Stokes (RANS) [13], and Large Eddy Simulation (LES) [14]. This analysis step is equally crucial as the choice of modeling technique in the previous step, as it significantly impacts the quality of the virtual real-time model. In addition to post-processing simulation results, Data-Driven Modeling (DDM), such as machine learning (ML), can be employed to simulate physical relationships either entirely or partially. This approach is known as Hybrid Analysis and Modeling (HAM). Utilizing DDM and ML techniques allows for the incorporation of data-driven insights into the modeling process, enhancing the accuracy and reliability of the virtual model [15].

Insight: Upon fully updating the virtual model, the simulation and analysis results can be seamlessly integrated into the chosen platform during the assessment phase (see Figure 8). Although there are limited resources discussing the specific methods of virtualizing analysis results, it is likely because many analyses software already incorporate this functionality.

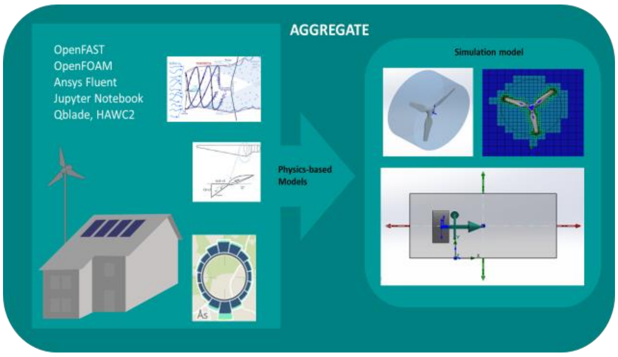
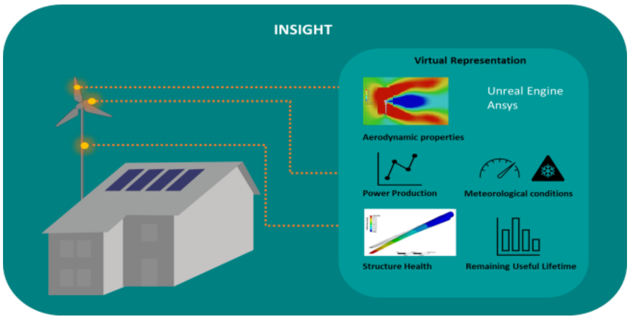


Fig. 7. The aggregate showing connection of virtual and real world.



Fig, 8. Visualization of the physical system, where the left part shows live 3D model using a game engine, and the technical data can be represented in a monitoring screen in a web application.

Act: By utilizing the visualization provided by the insight platform, a human user can acquire valuable knowledge for decision-making and effectively plan future actions based on predictive or prescriptive decision trees. Consequently, the user should be able to interact with the system state through a user-friendly interface. To achieve an autonomous decision tree, an additional supervising entity such as artificial intelligence (AI) is required to close the control loop through model-based decision-making. As illustrated in Figure 9, it should be possible for the human user to detach the AI as a supervisor and directly act upon the predictions derived from the analysis.

The figure shows a control loop, which can be modeled and executed quite easily in software like OpenModelica, or Python Flask.

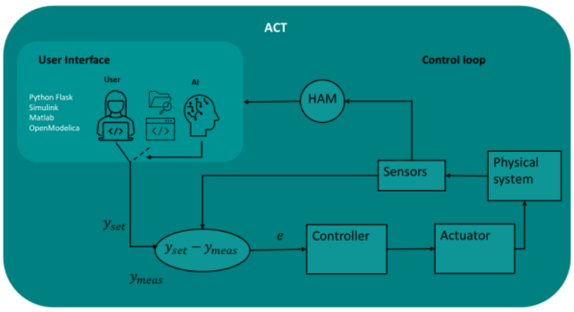


Fig. 9. Conceptual model a control loop implementation for autonomous DT.

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.

Overall, the Create, Communicate, Aggregate, Analyze, Insight, and Act steps form a continuous cycle where data is acquired, processed, analyzed, and visualized, leading to informed actions on the physical wind turbine system, while also facilitating feedback and improvement of the DT itself.

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