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Industrial digital twins in offshore wind farms

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Abstract

Digital twin technology, aligned with Industry 4.0 standard, has witnessed widespread adoption in various industries, notably in manufacturing. Meanwhile, the concept of digital twin itself is yet to be clearly defined in wind farm sector. Our primary contribution lies in investigating the potential for transferring knowledge of industrial digital twins for the wind farm industry. Through a comprehensive literature study, we explored the digital twin concept within the context of wind farm applications. Also, we conducted a comparative analysis of digital twin frameworks employed in wind farm and manufacturing sectors. We aim to identify commonalities and differences between these frameworks and to determine how they could be adapted to the unique requirements of the offshore wind sector. A case study is presented, wherein the Industry 4.0 standard framework, Asset Administration Shell (AAS), is conceptually applied to the wind farm sector. Additionally, we briefly explored the AASX Package Explorer and concluded that implementing the AAS could be a promising option for enhancing digital twin functionality in offshore wind farms, and for achieving interoperability in line with Industry 4.0 standard.

Keywords: Digital twins, Industry 4.0, Interoperability, Wind farms

Introduction

According to the Global Wind Report 2021, there was 743 GW of installed wind power capacity worldwide, and statistically, 2020 was the best year in history for the global wind industry with more than 93 GW of new installation (Lee et al. 2021). Indeed, wind power has its market among renewable energy industries as it is considered eco-friendly and sustainable. The urgency in realizing the Paris Agreement on the net zero target of CO_2 emission by 2050 is forcing the energy industry to continue to develop following technological advances. Energy industry has been moving forward by involving intelligent technology following the industry revolution in its application. In 2011, industry 4.0 was first introduced at the Hanover Fair, as a program of the German government (Xu et al. 2021). Industry 4.0 is driven by the Industrial Internet of Things (IIoT) and Cyber-Physical Systems (CPS) that utilize computer-based algorithms to control and monitor physical devices like vehicles, robots, machines, etc. Wind farm industry requires a fast change towards industry 4.0, powered by smart technology such as machine learning, big data, the internet of things, and digital twins to achieve the monitoring, automation and analysis of supply chains.

One of the features of Industry 4.0 is the capability to manage the entire life cycle of a product from the beginning to the end. This includes planning the initial needs of users and using their feedback to improve future designs. Digital twin technology is recognized as being able to realize this demand in the Industry 4.0 era (Salimbeni et al. 2022). Basically, digital twin is a virtual representation of a physical object with two-way communication and reflects live data of the physical object. Digital twins can be used for several purposes in the operation of offshore wind farms. It enables the integration of real-time data from various sensors, monitoring devices, and control systems deployed on floating wind turbines and associated infrastructure. By analyzing historical and real-time data, advanced analytics and machine learning algorithms applied to digital twins can help in early fault detection, diagnostics, and prediction of potential issues. For modelling, it creates dynamic and detailed simulations of the entire floating wind farm, particularly in changing environmental conditions, wave dynamics, and structural responses. It also facilitates communication and collaboration among different stakeholders, such as operators, maintenance teams, and management, through the digital twin platform. Digital twin technology can have a significant impact on the wind farm industry, as it may improve productivity, sustainability, safety, and reduce operation and maintenance costs (Stump 2020). This technology can also provide opportunities for the development of autonomous operations (Chen et al. 2021).

The application of digital twin technology requires a framework which is a communication architecture/platform to connect digital assets and physical assets. The framework is also critical in ensuring connectivity between the various companies involved in the development and operation of offshore wind farms. Building and operating an offshore wind farm involves several stakeholders, for example, a manufacturer for constructing the turbines, a maintenance company for maintenance work, a power plant company for power distribution, and the owner. All these stakeholders have their own way of communication within their company. They have their own "language" to store their data. The problem comes when one company needs to share their data with another company. Difference in "language" causes the data-sharing process to take longer. Consequently, it is time-consuming for a company to share their data with another company, which negatively impacts productivity. In Industry 4.0, there is a growing demand for all companies involved in one project to communicate in a similar and standard "language" in order to integrate automatically without human intervention. This ability is called interoperability where the computer systems or programs can exchange the correct information with each other and carry out the functions. Thus, a standardized framework for digital twins is needed to facilitate interoperability and ensure that computer systems can exchange data across sectors. Interoperability has proven to be highly beneficial in increasing productivity and effectiveness in the manufacturing industry, particularly concerning crucial functions such as condition monitoring, predictive maintenance, and product life cycle management. These same functions are also essential to the offshore wind industry. The lack of interoperability in the digital twin frameworks for offshore wind farms is a significant barrier that needs to be addressed. By transferring knowledge about interoperability from the manufacturing industry to offshore wind farms, industrial digital twins can be used to optimize the performance of offshore wind turbines.

The primary contribution of our study is to explore the potential for transferring knowledge of interoperable digital twins from the manufacturing industry to offshore wind farms, which will be addressed by focusing on these three objectives:

1. to define the concept of digital twins in offshore wind farms
2. to investigate the solution framework used for interoperable digital twins in the context of Industry 4.0
3. to conceptually apply the solution framework for offshore wind farms in the case study

The remainder of this paper is organized as follows. In "Method and material" section, we clarify the research method as well as the research materials. In "Results and discussion" section, we present our findings and discussion including the case study. Finally, the conclusion and an outlook for future work are presented in "Conclusion" section.

Method and material

To achieve our objectives and thus increase our understanding of digital twins in offshore wind applications, we proposed a research methodology based on a qualitative approach inspired by Verdouw et al. (2021). We integrated both a review study and a case study to demonstrate not only the existing potential but also to provide recommendations for the future. As displayed in Fig. 1, the research was conducted in three phases: (i) literature on the digital twin concept, marked in green, (ii) literature on digital twin frameworks, marked in blue, and (iii) a case study, marked in purple.

The method and material for each phase are defined as follows:

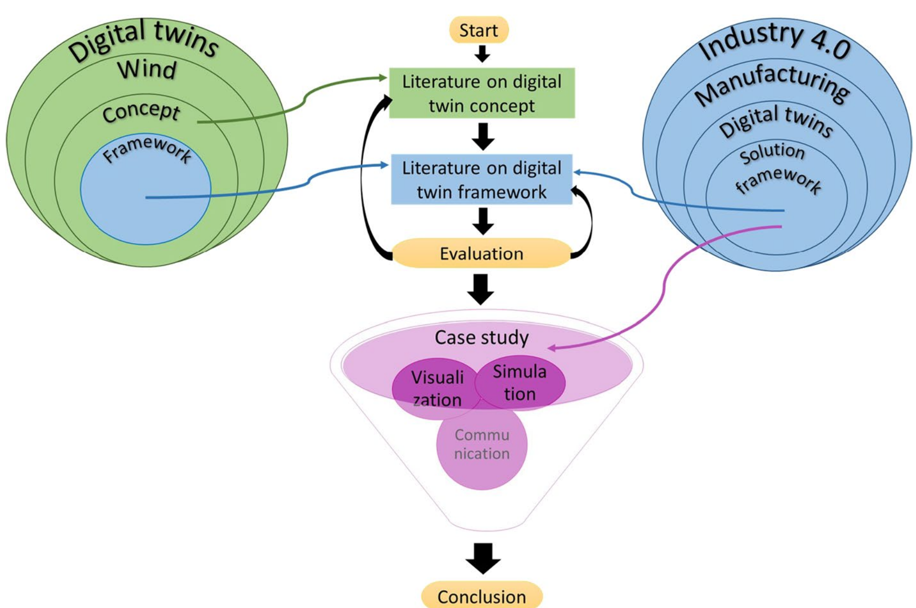

Fig. 1 A research approach for investigating interoperable digital twins in offshore wind farms

(i) we investigated the digital twin definition in offshore wind farms by conducting a narrative literature review based on a book chapter in Demiris et al. (2019). The green circles in Fig. 1 describe the selected materials covered in this phase. Digital twins, wind, and concept represent articles that discuss the concept of digital twins in offshore wind applications. First, we gathered articles mentioning digital twin/twins/twinning and wind in their titles. The existence of "wind" can be interpreted as wind turbine, wind energy, or wind power. Next, we selected articles that define the concept of digital twins in their application on offshore wind farms. Only articles in English that are included among accessible articles from the primary/original research have been reviewed. Then, we categorized the selected articles based on the purpose of using digital twins in offshore wind farms. The result of this phase is presented in "Digital twin concept in offshore wind farms". This phase aims to increase understanding of the digital twin concept from several applications in offshore wind farms.

(ii) since applying digital twin technology requires the digital twin frameworks, the next step was to look into the introduced framework in selected articles from phase (i), marked with the blue circle and blue arrow on the left side in Fig. 1. The investigation consists of how the framework was implemented, the specific purpose of the particular framework, and the benefits of the introduced framework. Then, we investigated a framework that has been built upon the Industry 4.0 standardization from other industries. The blue marks on the right side in Fig. 1 belong to the second phase. We began with Industry 4.0 standardization and selected the manufacturing industry as a benchmark. This is because intellectual and advanced technologies such as digital twins have been successfully achieved in this sector. The articles reviewed in this phase are limited to the implementation of the solution framework, not including the development of the framework. We present the implementation of the solution framework on several applications. The result of this phase is presented in "Comparison of digital twin frameworks in wind power and manufacturing industries". This review was conducted to provide an overview of how the solution framework can be advantageously developed in the manufacturing industry. Moreover, we evaluated the challenges faced in offshore wind farms from phase (i) that had been solved in the manufacturing sector using the solution framework in phase (ii). In other words, we built a parallel of challenges addressed in wind farm sector with similar problems addressed in manufacturing applications. This evaluation result is outlined in "Discussion: the interoperable digital twin framework for the offshore wind industry". This evaluation aims to highlight the feasibility of transferring the solution framework to a different domain.

(iii) we investigated an existing case study conducted by one of the co-authors in Haghshenas et al. (2023). The case study implements predictive digital twins in offshore wind farms and is adopted to demonstrate a high potential for the solution framework being applied in offshore wind farms. Purple marks in Fig. 1, including the purple arrow, belong to the case study. The comprehensive investigation focuses on three components: (a) the visualization in the form of 3D, 2D, and augmented reality (AR), which integrates the actual weather data, (b) the simulation of data processing, and (c) the communication protocol for connecting data from various sources. The purple arrow in Fig. 1 denotes that the solution framework set out in phase (ii) was conceptually applied to the case study. We also explored a tool called AASX Package Explorer to analyze how the tool handles interoperability. This phase result is presented in "Case study".

Results and discussion

In this section, we present the findings from the research approach discussed earlier. The first part defines the digital twin concept in the context of offshore wind farms. The second part compares digital twin frameworks applied in wind farms and manufacturing, then followed by a discussion of the interoperable digital twin framework for the offshore wind industry. The final part presents our case study.

Digital twin concept in offshore wind farms

Digital twins have been implemented in diverse sectors, such as manufacturing, health, meteorology, education, cities, transportation and energy (Rasheed et al. 2020). Basically, the digital twin is a virtual representation of a physical asset which can exchange information with others and reflects real-time data of the physical asset (Branlard et al. 2020a). Recently, researchers have categorized digital twins based on their specific applications. For example, Valk et al. (2020) conducted a structured literature review in order to develop a taxonomy of digital twins in general. Sjarov et al. (2020) systematically reviewed the digital twin concept in the industry, while Cooper et al. (2022) presented the maturity level of digital twins pertaining to its application and benefit. Verdouw et al. (2021) explored digital twins in smart farming describing the digital twin definition from two perspectives: the Internet of Things and the product life cycle. These studies show that the digital twin concept is defined according to its application.

As mentioned earlier, digital twins can be used for several purposes in offshore wind farms. For modelling, it enables to simulate the impact of different conditions on the performance of offshore wind turbines. For condition monitoring and control, the digital twin is continuously updated with real-time data from wind farms, allowing operators to make informed decisions and adjustments without the need for physical presence. Together with machine learning algorithms, the invoked time-series data can be used to estimate the power output and predict potential failures. Due to the application differences, we classified the digital twin concept into five perspectives, namely modelling, estimation, control, monitoring, and prediction, as shown in Table 1. In the early stages, digital twins are primarily used for modelling and estimation purposes, while in later stages, digital twins are utilized for controlling, monitoring, and predicting. Note that the implementation of digital twins in offshore wind farms is not limited to turbine-related components, such as blade and rotor, but also encompasses the entire systems such as pitch angle control, mooring system, gearbox, bearing, support structure, and drivetrain. Furthermore, the definition of digital twins used in offshore wind farms varies based on the specific application and components being considered. This segment aims to gain a deeper understanding of the digital twin concept in the context of offshore wind applications.

Table 1 Classification of digital twins based on their purposes

Main purpose	Applications	Sources
Modelling	H vertical axial wind turbine	LeBlanc and Ferreira (2020)
	Turbine blade	Chetan et al. (2021), Sahoo et al. (2017)
	Fatigue re-assessment on structure	Tygesen et al. (2018)
Estimation	Wind turbine loads	Branlard et al. (2020a)
	Wind speed	Hu et al. (2020), Li and Shen (2022)
	Mooring life tension	Walker et al. (2021)
	Remaining useful time of gearbox	Mehlan et al. (2022), Moghadam et al. (2021)
	Remaining useful time of power converter	Sivalingam et al. (2018), Zeitouni et al. (2020)
Monitoring	Gearbox	Xiangjun et al. (2020), Wadhwani et al. (2022)
	Uncertainties of structural dynamics	Augustyn et al. (2021), Ebrahimi (2019)
	Turbine substructure	Grosse (2019)
	Mooring system	Trueba et al. (2021)
	Wind turbines (farm)	Pargmann et al. (2018), Fahim et al. (2022)
Prediction	Wind turbine	Li et al. (2021), Iosifidis et al. (2021)
	Support structure	Wang et al. (2021), Momber et al. (2022)
	Electrical components	Oñederra et al. (2019)
	Gearbox	Zhao et al. (2021)

From a modelling perspective, LeBlanc and Ferreira (2020) presented a digital twin model of an H Vertical Axial Wind Turbine (H-VAWT) towards the experimental characterization. By applying the polymax curve filter in Siemens Test.lab software, they captured complex loading phenomena during the test process to update the finite element model. Here, the digital twin is clarified as a digital replica of a physical device to predict turbine response for dynamic blade pitching. For turbine blade design, Chetan et al. (2021) developed a multi-fidelity digital twin structural model of the turbine blade for system control and stable rotor operation using the OpenFAST framework. The digital twin method comprised observing the rotor from the design stage to the manufacturing, testing, and operation stages. Sahoo et al. (2017) reported a structural analysis of shear webs with a circular hole on a turbine blade using a finite element model in order to reduce material testing. Here, the digital twin is interpreted as a numerical model which is able to simulate a physical behaviour under a certain environmental condition without experimental cost. Tygesen et al. (2018) introduced the digital twin model for fatigue re-assessment on wind turbine structures using Structure Integrity Manager (SIMA) software to analyze and detect the inconsistency between the model and the real measurement. The authors introduced five levels of digital twin development in offshore wind farms, namely screening and diagnostics, finite element model updating, wave load calibration, quantification of uncertainties, and accumulated fatigue monitoring. Here, the digital twin is a reflection of the current state of the structure that can be analyzed to predict the future behavior of the structure.

From an estimation perspective, Branlard et al. (2020a) defined digital twin in offshore wind farms as a digital equivalent of the actual turbine combining measurements from the physical turbine and the numerical model to estimate the turbine status and track the life cycle of the physical assets. Using the OpenFAST framework, Branlard et al. (2020b) estimated wind turbine loads by applying the Kalman filtering technique with measurement signals of rotational speed, pitch angle, generator torque, and tower-top acceleration. For wind speed prediction, Hu et al. (2020) applied digital twins to predict time-series of wind speed based on ensemble empirical model decomposition (EEMD), long short-term memory (LSTM) neural network, and the Bayesian Optimization (BO) method. Based on digital twin technology, Li and Shen (2022) proposed a novel wind speed-sensing methodology for wind turbines by applying a series of estimators, verifiers, setters, and selectors called DTSense. Here, the digital twin is a digital replica that collects and stores operating data based on deep learning algorithms from physical assets to illustrate how an Internet of things (IoT) works through its life cycle. Furthermore, Walker et al. (2021) developed a digital twin of the mooring life tension using a state-of-the-art data-driven method to improve lifespan and safety. They designed the first digital twin to predict the behavior of the healthy system compared with the actual one, then subsequently constructed the second digital twin to forecast the future axial tension of the mooring line using existing data for safety purposes. Referenced by Oneto et al. (2018), here the digital twin is defined as a specific type of model able precisely to copy a physical system and learn the historical behavior to forecast the future behavior of the system. Moreover, Mehlan et al. (2022) employed bond graph modelling techniques to create a digital twin of wind turbine gear stages, which was further utilized for the implementation of real-time virtual sensing. The goal of this approach was to estimate the remaining useful life (RUL) of the gear and bearing components through the application of fatigue damage models. Sivalingam et al. (2018) developed a methodology for RUL prediction for prognostic and diagnostic health of a power converter Insulated-Gate Bipolar Transistor (IGBT) on offshore wind turbines based on digital twin technology. Here, the digital twin is a virtual representation of a physical asset storing real-time simulation data in the framework to predict the RUL as a means of optimization and improved decision-making.

From a control perspective, Parvaresh et al. (2020) applied a digital twin for the control system of pitch angle in a variable speed wind turbine operating at wind speeds above the rated level. The authors were able to control the pitch angle via a digital twin by introducing a deep-learning backstepping controller with software-in-loop (SIL) and hardware-in-loop (HIL) approaches. In another report, Zeitouni et al. (2020) improved a novel adaptive controller for the pitch angle control of a wind turbine plant by augmenting the active disturbance rejection controller (ADRC) to evaluate the wind speed error and the difference between HIL and SIL results. Here, the digital twin in wind turbine systems consists of virtual assets as well as physical assets and connection data that tie, reflect, and control each other.

From a monitoring perspective, Xiangjun et al. (2020) focused on anomaly detection of wind turbine gearboxes by merging the benefits of model simulation technology and data-driven methods to improve operational reliability and minimize operation and maintenance (O&M) costs. Wadhwani et al. (2022) discussed the concept of a digital twin framework for forecasting the failure of turbine gearboxes with updated real-time Supervisory Control and Data Acquisition (SCADA) data. Here, the digital twin is defined as a virtual space of a physical world that is built digitally utilizing real-time data to monitor the physical assets and simulate the behavior of a wind farm in real-world entities. Augustyn et al. (2021) leveraged digital twins to monitor and update the uncertainties related to the load-modeling parameters and structural dynamics in fatigue damage accumulation using Bayesian pre-posterior theory. In discussing the challenges of developing a digital twin model, Ebrahimi (2019) strongly suggested applying uncertainty and intelligent algorithm tools to modify the digital twin platform in order to be closer to the real one and make it feasible. Grosse (2019) reported the development and benefits of the digital twin concept from Building Information Modelling (BIM) for monitoring and inspection techniques in wind turbine substructures. Here, the digital twin is defined as an essential step in accurately and precisely assessing the structural integrity of pre-existing structures to support decision-making and optimal designs. Trueba et al. (2021) introduced an R&D project called MooringSense, a concept for floating offshore wind mooring system integrity management based on control, monitoring, and digital twin technologies to reduce expenses, optimize O&M, and increase energy production. Pargmann et al. (2018) applied digital twins to integrate not only technical information, such as the data streams from different sensor types but also business information to monitor and analyze a complete wind farm based on Cloud-technologies. Fahim et al. (2022) proposed a machine learning-based digital twin model using a 5G Next Generation Radio Access Network to monitor wind turbines, estimate the generated power, and create a wind turbine model in terms of wind speed. Here, the digital twin is a user-friendly model that provides all updated and integrated information based on a cohesive and sound big data processing approach to allow the user a real-time view and to implement risk-based integrity management plans.

From a prediction perspective, Li et al. (2021) reported research on digital twins and collaborative cloud and edge computing applied in the operation and maintenance of wind turbines for fault prediction and diagnosis. Using real-world, 1-s wind speed data, Iosifidis et al. (2021) explored the effect of wind turbulence as well as wind speed on semiconductor devices of direct-drive wind turbines resulting in fatigue. Wang et al. (2021) focused on investigating the support structure of offshore wind turbines to prevent unexpected damage and reduce maintenance costs by analyzing fault diagnosis, condition-based maintenance, and RUL prediction. Here, the digital twin is defined as a promising tool for understanding the undergoing mechanisms of structures for the purpose of fault prediction and establishing a diagnosis model to schedule the maintenance plan and support decision-making methods. Furthermore, Momber et al. (2022) applied the digital twin concept for the prescriptive maintenance planning and control monitoring of surface protection systems on wind turbine towers. Montoya et al. (2022) developed a wind turbine digital twin model for failure prognosis by comparing actual data from SCADA and simulated data from software combined with artificial intelligence algorithms in the digital twin creation. Oñederra et al. (2019) discussed a medium voltage (MV) cable model of different electrical components, such as power converter, generator and transformer, on wind farms in order to imitate the real asset in terms of preventive maintenance. Here, the digital twin is the use of abundant data about the performance and behavior of physical assets to integrate them in a multi-disciplinary simulation within a digital environment which allows for predicting its performance. The gearbox is one of the crucial and risky parts that require special treatment to prevent fatigue and damage as it plays a significant role in connecting turbines and generators for producing power. Zhao et al. (2021) introduced a CapsNet-based deep learning scheme for a data-driven fault diagnosis method for digital twins of a wind turbine gearbox, including single fault and coupling fault. Moghadam et al. (2021) proposed a multi-degree of freedom torsional model of a drivetrain system in the prediction of gearbox RUL using a 5 MW reference drivetrain. Here, the digital twin is a highly accurate but computationally fast model of the system, which can update itself by the online measurement and predict its future behavior.

In addition to those research efforts, summarized in Table 1, there is advanced research by Chen et al. (2021) discussing a human-cyber-physical system toward wind turbine operation and maintenance in the context of achieving Industry 5.0 technology standards. Highly effective training of AI through machine learning is required for Industry 4.0 digital twin technology. Here, human intelligence (HI) was developed, where a high-level decision made through a human–machine interface breaks the autonomy. This idea could be a promising tool for the improvement of an advanced wind farm, but only if there is a reliable framework that can connect all assets and industries related to wind farms, providing the so-called interoperability. Thus, the digital twin is not only utilized for modeling, control monitoring, and/or predictive maintenance, but also as a management tool for the life cycle management of wind farms itself (Salimbeni et al. 2022).

Comparison of digital twin frameworks in wind power and manufacturing industries

In order to leverage digital twins, it is essential to establish a framework that facilitates data storage and communication between digital and physical assets. By analyzing recorded operational data, it is possible to anticipate the future behavior of physical assets, while historical data can be used to predict potential device failures. The data stored in the framework can serve as a foundation for developing newer and more sophisticated devices. This segment explores various frameworks for implementing digital twins, including those employed in offshore wind farms and in the manufacturing industry. It also examines the potential for deploying these frameworks in offshore wind farms and highlights similarities and differences between them, as well as how they can be tailored to meet the distinctive requirements of the offshore wind sector.

Digital twin frameworks in offshore wind farms

Branlard et al. (2020b) utilized OpenFAST linearizations to build a linear state-space model, including degrees of freedom (such as the shaft rotation and the tower-top motion) and considerations of the offshore environment for real-time load and fatigue estimation on wind turbines. OpenFAST is a framework, an open-source wind turbine simulation tool, a multi-physics and multi-fidelity tool, that couples dynamic response (fluid, control and electrical system, and structural dynamics) of wind turbines. Chetan et al. (2021) also utilized the OpenFAST framework to capture the dynamics of the as-build design of the turbine blade due to various root bending moment conditions experienced during simulation. The significant benefit of OpenFAST is that it can automatically linearize a wide range of conditions, including states, inputs and outputs. Another benefit of OpenFAST is that it can perform simulations with only a few DOF (from 2 to 30 DOF) as proven by Branlard et al. (2020a) comparing 2 DOF and 16 DOF in a wind turbine, whereas traditional FEM requires a thousand DOF.

Parvaresh et al. (2020) presented a digital twin framework that combines hardware-in-loop (HIL) and software-in-loop (SIL) techniques for pitch angle control of variable-speed wind turbines. HIL involves testing software systems on cloud-based test benches that receive inputs from physical assets, while SIL is a cost-effective method of testing code in a simulation environment. The authors proposed the use of a deep deterministic policy gradient (DDPG) based nonlinear integral backstepping (NIB) method supported by model-free control (MFC) to minimize the difference between the SIL and HIL environments. When SIL is an entirely virtual format, HIL involves data from sensors as if seeing real driving circumstances. The authors use SIL and HIL to make sure controllers can work in real-time situations and to model how a closed-loop system behaves in software. Further advanced work, Zeitouni et al. (2020) augmented the active disturbance rejection controller (ADRC) to compensate for high aerodynamic variations, mechanical stresses on the drivetrain, and unknown uncertainties.

Pargmann et al. (2018), Li et al. (2021), and Fahim et al. (2022) utilized cloud computing technologies as a digital twin framework for offshore wind farms. Pargmann et al. (2018) gathered all data from several sensors in Raspberry Pi and SCADA to the cloud IoT interface of SAP Cloud Platforms (SCP). The authors also built a SAP Enterprise Central Component (ECC) named ZEIT cloud to store external information (weather forecasts, exchange rates, flight of birds, etc.) and other data (business intelligence, customer relationship management, supply chain management, enterprise resource planning) related to the offshore wind farm industry. They argued that the edge-cloud collaboration approach could integrate technical and business data within a single digital twin by using augmented reality (AR) to visualize wind farm data.

Li et al. (2021) presented a framework for real-time monitoring of O&M in offshore wind farms, consisting of three layers: data source, edge computing node, and public or private cloud computing. The benefit of edge-cloud collaboration for O&M is that it enabled continuous adjustment of simulation results, as the model is based on the zero component feature of the equipment. Moreover, Fahim et al. (2022) proposed a 5G-Next Generation-Radio Access Network (5G-NG-RAN) assisted cloud-based digital twin framework of Microsoft Azure for investigating wind farms. The study concluded that the use of the cloud framework enabled effective monitoring through the provision of data from supervisory control and data acquisition units in each turbine of a wind farm.

Tygesen et al. (2018) utilized a state-of-the-art software called Structural Integrity MAnager (SIMA) as a digital twin framework to create a digital twin for the structural monitoring systems. SIMA is able to update digital twins according to the structural behaviour with the Bayesian-based Finite Element model and to perform the wave load calibration. Using SIMA, they update the mass and stiffness parameters of digital twins in order to minimize the discrepancy between the predicted and measured parameters. The advantage of SIMA is that it enables coupling digital twins directly with the real measurements, analyzing and detecting inconsistencies between the digital and real measurements.

Trueba et al. (2021) proposed the MooringSense concept for implementing more efficient integrity management strategies for offshore wind mooring systems. The

MooringSense in digital twins consists of a high-fidelity fully coupled model divided into two aspects: predicted loads (virtual loads prediction, synthetic rope properties update, and floater motion prediction) and O&M data (remaining useful data, local damage calculation in chains, and mooring analysis) for decision making. MooringSense presented the updated condition information of the mooring systems and an approach for reducing uncertainties, performed under both static and dynamic offshore wind farm conditions. In addition to serving as a mooring system digital twin, the advantage of the MooringSense concept is the development of a smart motion sensor, a structural health monitoring (SHM) system, and control strategies on the wind turbine and farm levels.

Walker et al. (2021) applied (state-of-the-art) data-driven models (DDMs) as a digital twin framework to identify long-term drifts in the mechanical response of mooring lines for offshore wind turbines. The DDM technique utilizes the injection of configurator model components into the model dynamically, based on data received from external systems such as catalog systems. DDMs were used to improve computationally aware real-time monitoring systems for mooring lines by analyzing existing data of input–output behaviours to predict future axial tension of mooring lines. With DDMs, the framework has the potential to identify two approaches, the traditional machine learning method and the deep learning method, in order to predict the expected behavior of the healthy system, to be compared with the factual one. The benefit of DDMs is increased efficiency as they reduce cost and time to market by eliminating manual construction of model components, instead dynamically updating the model with changes in the catalog system.

All existing frameworks summarized in Table 2 focus only on the data connectivity between digital assets and physical assets, enabling the digital model to present the physical asset in terms of real-time data. To realize digital twins in the Industry 4.0 standard, not only connectivity is required, but also the ability to exchange correct information among the companies, known as interoperability. In the offshore wind farm industry, there are several companies involved in the process of construction, operation and maintenance, such as manufacturers, suppliers, and customers. Even within one company, it is challenging to harmonize, understand, and use these pieces of data together. Besides, different companies use different applications and a different "language" for the same asset aspects. The increased complexity of exchanging data across companies and supply chains requires interoperable digital twins following Industry 4.0

Table 2 Summary of digital frameworks implemented in offshore wind farms

Frameworks	Purposes	Sources
OpenFAST	Estimation	Branlard et al. (2020a), Branlard et al. (2020b)
	Modelling	Chetan et al. (2021)
HIL and SIL	Control	Parvaresh et al. (2020), Zeitouni et al. (2020)
Cloud computing technology	Monitoring	Pargmann et al. (2018), Fahim et al. (2022)
	Prediction	Li et al. (2021)
Structural Integrity MAnager (SIMA)	Modelling	Tygesen et al. (2018)
MooringSense	Monitoring	Trueba et al. (2021)
Data-driven model	Estimation	Walker et al. (2021)

standardization. Interoperable digital twins not only simplify the process of exchanging data across sectors but also increase the transparency, adaptability, and flexibility of data. Data interoperability can be achieved through interoperable digital twin frameworks. The interoperable digital twin is not a new idea in the manufacturing industry: the implementation of interoperable digital twins has been successfully achieved using a standardized framework. In the following segment, we describe the solution framework that is required in offshore wind farms in order to achieve interoperable digital twins facilitating engineers in decision-making.

Digital twin framework in the manufacturing industry

In order to realize interoperability in digital twins, a standard is required, allowing similar information to be applied in more than one sector. Standardization and interoperability strategies are key to success in implementing digital twins in the Industry 4.0 era. Asset Administration Shell (AAS) is a framework that has been promoted as the implementation of digital twins for the standardized Industry 4.0 to facilitate interoperability within one organization and across enterprise boundaries by allowing uniform access to the information and behavior of an asset (Geschäftsstelle 2018). Essentially, AAS is a machine-readable, technology or device-agnostic description of a component that provides access to all of its properties and functions. AAS consists of several submodels pertaining to its structure, which describe the asset's functionalities and information, such as parameters, properties, status, characteristics, and commercial and technical functionalities (Sakurada et al. 2021). AAS defines a meta-information model for Industry 4.0 known as the Reference Architectural Model for Industry 4.0 (RAMI 4.0), built upon properties standardized under IEC 61360 (Redeker et al. 2020). This segment investigates how AAS has been widely applied in the manufacturing industry.

AAS has three types based on the pattern of interaction, namely passive, reactive, and proactive, as seen in Fig. 2. In the passive type, AAS operates as a static file or file package, with asset data being stored in a uniform data format. The reactive type indicates

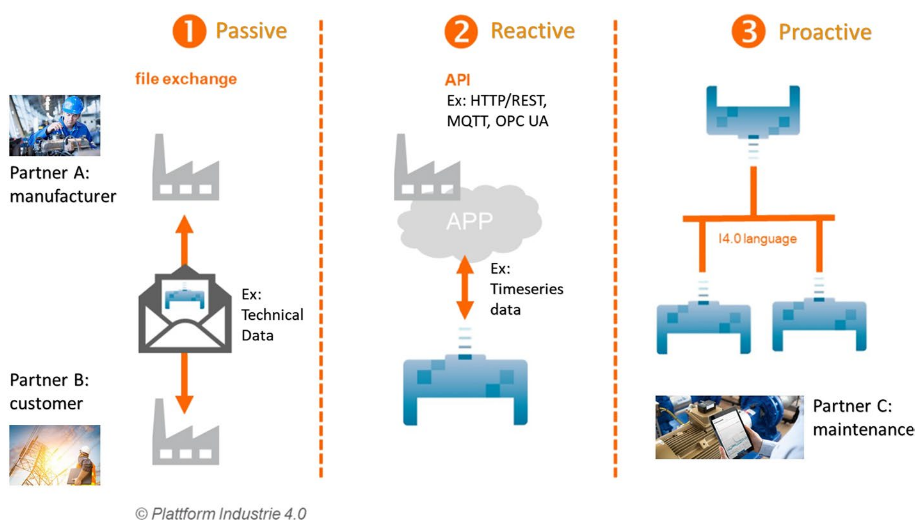

Fig. 2 Asset administration shell types (Geschäftsstelle 2018)

a scenario where AAS can exchange information with other AASs or software applications through Application Programming Interface (API). In the proactive type, AASs can autonomously associate with each other via a standardized interface with a common syntax and semantics foundation, thereby facilitating peer-to-peer interaction among AASs (Ye et al. 2021). In the manufacturing industry, the interoperability of AAS is used for several purposes, such as production line design, life cycle management, condition monitoring, predictive maintenance, value chain, and autonomy.

From a modeling perspective, Lu et al. (2021) presented a general platform based on AAS. They focused on the communication layer by using Open Platform Communication United Architecture (OPC UA) and on the information layer by using Automation Markup Language (AutomationML) in RAMI 4.0 for modeling AAS. The general AAS platform consists of three layers for a production line design. The first one is the asset layer, containing two different industrial robots with their controller and a digit control machine tool. The second one is the AAS layer containing a single AAS of all assets. The third one is the application layer consisting of the AAS modeling mode and the application scenario mode, which is to develop device AAS, verify specific scenarios, and order robots to work with Computerized Numerical Control (CNC). The AAS platform has platform control and platform communication between AAS and the device, also across AASs, by applying OPC UA clients and OPC UA servers which are connected in platform control. Furthermore, Ye and Hong (2018) also built an architecture for the integration of manufacturing processes using OPC UA and AutomationML. They refined RAMI 4.0 into a four-layer architecture. The first one is the enterprise layer, which is a combination of business and function layers of the RAMI 4.0 model. The second one is the information layer for data management on operation and maintenance, system configuration, and connectivity with other devices, to optimize decision-making. The third one is the communication layer, for establishing information exchange paths between user applications and field devices. The fourth one is the field layer which consists of the physical asset, e.g., sensors, controllers (PLC), actuators (robots), etc. The authors applied this architecture to a use case involving two conveyor belts for process hauling and two robot arms for the pick-and-place. They successfully integrated robot and conveyor engineering data using AutomationML and addressed the integration of Wi-Fi and Ethernet Powerlink protocols using OPC UA. Moreover, Lüder et al. (2020) leveraged AAS's role as the system integrator of engineering data logistics on advanced production systems. They presented a method for the implementation of AAS in the context of Industry 4.0, utilizing it in an ultrasonic measurement cell and its components within a steel mill as a case study. The method employed AutomationML to centralize the engineering data storage and to exchange data throughout the chain for the production process. The method realized a more efficient system for identifying, representing, and integrating engineering data. The authors concluded that AAS, due to its standardization, represents a simple yet effective technology for integrating production system engineering tools in an engineering network. Panda et al. (2018) presented OPC UA to host the AAS and provide a semantic dataspace for each asset in integrating plug-and-produce components. OPC UA was utilized to integrate all the OPC functionality into one extensible framework, to clarify the communication mechanism through a publisher–subscriber model or a client–server, to connect the information in several ways by expanding supplementary vendor-specific information to the OPC UA base model, and to allow assets to be found across the production system. They concluded that the use of UPC UA in the communication protocol of AAS allowed easy integration of plug-and-produce components into the network without any network-specific preconfiguration. Birtel et al. (2020) developed a method for transforming passively communicating product memory into an active digital object memory model (ADOMe) utilizing AAS as the semantic interface for interoperability. They carried out a use case where the product can be remotely discharged within the manufacturing process due to a defect. OPC UA was used in AAS to enable devices with OPC UA communication capability to access AAS information across the hierarchy. The authors discovered that the integration of ADOMe using AAS enables products to communicate with each other individually and remotely, thus improving the overall functionality and efficiency of the manufacturing process. Motsch et al. (2021) implemented the use of AAS in the context of the electrical energy consumption interface in modular skill-based production systems. They applied the reactive type of AAS with a passive API as a software adapter, whereby a specific AAS metamodel-compliment structure was able to represent a given component-specific interface. Information related to energy measurement from a Cyber-Physical Production Module (CPPM), smart sensors, and an Infrastructure Node (ISN) was transmitted directly to the AAS energy submodels. To facilitate this, the authors employed OPC UA for communication between CPPMs, ISNs, and AAS, resulting in the aggregation of OPC UA-Servers. They also presented the proactive type of AAS for the communication system between CPPM and ISN to provide information on energy consumption for skill execution decisions or energy-related condition monitoring and dynamic interaction with other components.

From a Product Lifecycle Management (PLM) perspective, Marcon et al. (2019) applied AAS to present case studies focusing on interconnecting sensors installed in the SmartJacket, on how Digital Factory (DF) components can operate and communicate with each other within the entire value chain. They analyzed the AAS model formation from the perspective of identification, configuration, communication, condition monitoring and safety. The authors proposed the integration of AAS into a central component, specifically a smart wireless sensor, in the context of implementing a SmartJacket system. By integrating AAS directly into the data concentrator of the smart wireless sensor embedded in the jacket, the authors argue that it is more effective for the SmartJacket system to communicate with the central control component (the central communication element behaves like an edge interface) and for the AAS to be physically included within the system. This approach improves the functionality and efficiency of the SmartJacket system by allowing for seamless communication and integration of AAS into the system. In the CPS era, a product not only performs PLM but also Application Lifecycle Management (ALM) which is the PLM of computer programs involving software architecture, software testing and maintenance, etc. Deuter and Imort (2020) utilized the AAS implementation to establish a new strategy named Plm4AAS in order to integrate PLM/ALM datasets in a single product model using Open Services for Lifecycle Cooperation (OSLC). The authors presented a method for the semi-automatic generation of PLM-related data within the framework of AAS. The proposed approach allows for the configuration of basic needs for PLM integration in AAS, thus enabling the definition of relationships between all data while importing it into the AAS data model. To evaluate the proposed method, Deuter and Imort (2021) conducted a case study at the SmartFactoryOWL, where they produced a sample product (SmartLight). The results of the study demonstrated the effectiveness of the proposed approach in generating PLM-related AAS data in an order-controlled production process. Göllner et al. (2021) applied AAS for the generation of dynamic simulation models in order to aggregate all information, including the structural data about a machine for maintaining the product across its life cycle. The proposed concept was able to generate the dynamic simulation model automatically built upon the standardized and interoperable digital twins, whereby all necessary data is mapped into the AAS structure. They established the simulation model description (SMD), where all data extracted from the AAS meta-model in the digital twin gateway was gathered to generate the simulation model for a particular simulation tool. They declared that the proposed concept entailed particular benefits for individual machine solutions with similar components, which is able to reduce the time consumption on manual efforts. Rauh et al. (2022) implemented AAS as an artificial intelligence (AI) asset management solution pertaining to AI life cycle management in the manufacturing industry. They argued that the AAS Standard facilitates and allows for streamlining time-consuming integration efforts in the plug-and-produce process. The concept of AAS allows the direct integration of all types of assets within a single information model. It is able to scale heterogeneous infrastructure while confirming reusability and reproducibility in terms of life cycle management. They declared that the AI model supported by the AAS standard offered a high degree of automation and interoperability on digital twin technology without requesting new system boundaries through communication language and the standardized API.

From a maintenance perspective, Cavalieri and Salafia (2020b) proposed an approach using the AAS concept to realize interoperability between different manufacturers and devices and to apply generic functionalities for a predictive maintenance solution on a smart factory. The approach relies on the AAS model and logical block (LB) concept which is an element modular categorizing the functionality related to the maintenance aspect, namely data manipulation or data acquisition. AAS presents the information in a uniform and semantically annotated manner, resulting in generic LB functionalities being applied by an asset using any suitable solution exposed by a standardized API. They concluded that the LB and AAS applied in the predictive maintenance model were able to define the maintenance actions to improve the flexibility level of production. Lang et al. (2019) utilized AAS to support humans during the maintenance process. The AAS submodel consists of the procedure-based maintenance approach providing the user with a standardized description of necessary equipment, tools, procedures, safety concerns, etc, for maintenance. They applied OPC UA as the communication protocol in AAS due to its vendor independency and its service-oriented architecture, for the industrial towel folding machine in SmartFactoryOWL as the use case. The AAS submodel is performed by updating AAS status, inputting the maintenance data log, and by supplying feedback to improve the life cycle process. Tantik and Anderl (2017) proposed an approach combining AAS and the World Wide Web Consortium (W3C) specification to achieve a uniform structure for industrial CPS. The required functionality consists of five main segments, namely for representation, communication to internal assets, communication to external CPS, security, and a portion for capability improvement, in which AAS provides an independent segment for data management. The use of AAS is highly suitable for standardization without interrupting the entity functionality. The proposed approach is implemented to store all information of the production process for the product life cycle, to customize the data model flexibly, and to access the required information automatically. As the use case for remote maintenance, the authors applied the approach to the robot arm.

From a monitoring perspective, Casado and Eichelberger (2021) merged the standardized AAS with existing components—a vendor-neutral monitoring frontend (micrometer) and IIoT protocols such as message queuing telemetry transport (MQTT)—on a runtime monitoring approach for devices and services in Industry 4.0 installations. The micrometer was utilized to provide runtime measures uniformly, MQTT was used for soft real-time streaming, while the monitoring results were shown in terms of AAS structures so that stakeholders were able to access the desired and monitored information through polling. The approach facilitated access to the monitored properties for individual services and devices, also as a fundamental feature for efficient aggregation of all installation elements. Pethig et al. (2017) applied AAS as an information model on the PLC of a work cell for condition monitoring of a servo motor in order to enhance the efficiency and flexibility of adaptable cyber-physical production systems (CPPS). The AAS is used to simplify the integration of the work cell into services and to automatically choose the right signals and configure parameters, i.e., thresholds of the maximum torque, thus shortening the time consumption. An OPC UA Client was utilized for the communication protocol in AAS to connect the AAS on the PLC. The authors concluded that the implemented AASs were able to monitor the condition of the servo motor and detect the exceeded thresholds. Rehman et al. (2022) implemented AAS in controlling the functionality of an intelligent testing process in the production system for small to medium enterprises (SMEs) which depend significantly on testing processes for their low volume but highly bespoke products. The implementation of the AAS involved observing the behavior change on the asset, thus directly controlling the behaviour of a production process. The server shell of the AAS consisted of all information about the related expressions, settings, parameters, and configurations of the physical assets to request the necessary API for executing the skills. The authors concluded that the presented implementation of AAS type 2 enabled a decrease in the required time for setting up a new testing process and for controlling the testing operation.

From an autonomy perspective, Herzog et al. (2020) proposed architecture of an autonomous adapting machine (ADAM) using AAS, particularly for the use case, a metal sheet cutting system, in order to minimize the effort on planning, implementation, communication, and recommissioning. AAS is utilized to manage the variability and interoperability among the machines and components, thus performing the changing requirements automatically. Ding et al. (2021) demonstrated a technology architecture based on a blockchain using the AAS model for digital management, production plan and process, controlling the manufacturing task, and trusted autonomous execution. They established an AAS blockchain sub-model to facilitate communication with the system to complete distributed authentication in real operation pertaining to the establishment, operation and maintenance of a workshop. Seif et al. (2019) implemented

AAS as a means of creating a connector between the physical world and the IIoT world in mini-factories. The AAS approach aimed to provide a comprehensive representation of the asset, including the technical functionality and the relationship with other assets. The methodology was demonstrated through a case study conducted at the Model Factory @ARTC (Advanced Remanufacturing and Technology Centre) in Singapore, where a gearbox factory consisting of three distinct processes (fabrication, warehousing, and assembly) was selected as the testbed. The study employed an IoT platform with RESTful API connectivity, enabling automatic storage and communication protocol, to connect the physical assets to the digital assets represented by the AAS. As a result, the factory manager was allowed to identify available information for specific assets and the frequency of data updates. The authors argued that the methodology is highly suitable for the manufacturing industry towards Industry 4.0. Stock et al. (2021) applied AAS in 5G architecture-enabled cyber-physical production systems (CPPSs) to represent virtualization technology. The AAS was utilized as a unifying component to confirm a consistent information model in the CPPS for interoperability among the integrated components, which was initially carried out in different ICT and operation technology (OT) fields. Walter et al. (2022) presented an architecture applying AAS based on RAMI 4.0 for the integration of cable-driven parallel robots (CDPRs) in a system of industrial cyber-physical systems (ICPS). The purpose of using AAS is to provide the information associated with CDPRs on the communication and information layer of RAMI 4.0 using OPC UA in order to realize semantic interoperability.

The deployment and advancement of new technology in Industry 4.0 add high complexity. It not only relates to how the data is adequately structured and represented, but also to the communication methodology for exchanging the information in order to integrate the data from multiple vendor-based systems (di Orio et al. 2019). This segment has explored the advantages of applying AAS from existing studies from several perspectives, as seen in Table 3. Most of them address the simplicity of AAS on communication, integration, connectivity, interoperability, and autonomy. These apply to life cycle management, production line, condition monitoring, predictive maintenance, and autonomous execution in manufacturing plants. Existing studies have proven that AAS decidedly works in terms of standardization and interoperability between automated industrial systems and CPSs according to Industry 4.0 (Iñigo et al. 2020). The fruitfulness of AAS in the manufacturing industry can significantly impact other industries, particularly the offshore wind industry. In the following segment, we investigate the greater potential of using interoperable AASs in offshore wind farms in the future.

Discussion: the interoperable digital twin framework for the offshore wind industry

The wind energy industry, including both onshore and offshore wind farms, has yet to incorporate digital twins based on AAS. However, with the transfer of knowledge regarding AAS implementation from the manufacturing industry, there is significant potential for the development of interoperable AAS in offshore wind farms. In this segment, we discuss the possibility of addressing the challenges faced in offshore wind farms (as described in "Results and discussion" and "Digital twin frameworks in offshore wind farms") that had been achieved in the manufacturing sector by using AAS, as outlined in "Digital twin framework in the manufacturing industry". The summary is

Table 3 Summary of the AAS implementation

Main perspective	Sources	Focus on
Modelling	Lu et al. (2021)	Communication and information layers
	Ye and Hong (2018)	Enterprise, communication, and information
	Lüder et al. (2020)	Data exchange along the chain
	Panda et al. (2018)	Integration of plug-and-produce system
	Birtel et al. (2020)	The ADOMe integration
	Motsch et al. (2021)	Communication system
Management	Marcon et al. (2019)	Interconnection of SmartJacket sensors
	Deuter and Imort (2020, 2021)	PLM/ALM integration
	Göllner et al. (2021)	Generate the dynamic simulation
	Rauh et al. (2022)	AI life cycle management
Maintenance	Cavalieri and Salafia (2020b)	Interoperability of smart factory
	Lang et al. (2019)	The connectivity of life cycle processes
	Tantik and Anderl (2017)	An integrated data model
Monitoring	Casado and Eichelberger (2021)	The integration patterns
	Pethig et al. (2017)	The integration of CPPS
	Rehman et al. (2022)	Integrating intelligence into test process
Autonomy	Herzog et al. (2020)	Interoperability among machines
	Ding et al. (2021)	The transparency of integrated data
	Seif et al. (2019)	Automated configuration of sensor system
	Stock et al. (2021)	Interoperability among components
	Walter et al. (2022)	Integrate a new class in ICPS system

shown in Table 4 The goal of this discussion is to explore the feasibility of applying AAS in offshore wind farms in order to improve efficiency and productivity. By leveraging the existing solutions from the manufacturing sector, we can potentially mitigate the challenges in offshore wind farms, such as high maintenance costs, limited accessibility, and safety concerns.

For example, Li et al. (2021) presented a digital twin of wind turbines by combining cloud and edge computing technology for fault prediction in general. Montoya et al. (2022) established a digital twin by comparing actual data from SCADA and simulated data from software to be analyzed. In this case, AAS provides the automatically updated storage and the communication protocol connecting the real asset to the digital asset, something which has been investigated by Seif et al. (2019) in mini-factories. Additionally, when it comes to identifying fatigue issues in particular parts, i.e. the support structure or tower (Wang et al. 2021; Momber et al. 2022), the gearbox (Zhao et al. 2021; Moghadam et al. 2021), and the semiconductor material (Iosifidis et al. 2021), can refer to the study by Motsch et al. (2021). This study is called "electrical energy consumption interface in modular skill-based production systems with the Asset Administration Shell," and it shows that AAS can provide a customized interface for this purpose. Predicting the failure on the device before it occurs significantly impacts the turbine lifetime and prevents the consequent downtimes. Any maintenance activities affect the generated power of wind turbines significantly, which in turn directly impacts revenue. Especially for offshore wind farms, corrective maintenance requires specific resources, such as vessels with a gangway, crane, and helideck, which are not always available, generating costs. Predictive maintenance is beneficial in providing an opportunity to reduce

Table 4 Summary of relevant challenges in wind farms and manufacturing sectors

Wind farms			Manufacturing		
Purposes	**Cases**	**Sources**	**Cases**	**Sources**	**AAS roles**
Fault prediction in general	Cloud and edge computing tech.	Li et al. (2021)	In mini factories	Seif et al. (2019)	Automatically update storage
	Comparing actual and simulated data	Montoya et al. (2022)			
Fatigue identification in particular parts	The support tower	Wang et al. (2021), Momber et al. (2022)	Electrical energy consumption interface	Motsch et al. (2021)	Provide a customized interface
	The gearbox	Zhao et al. (2021), Moghadam et al. (2021)			
	Semiconductor	Iosifidis et al. (2021)			
Condition monitoring and control	Ppitch angle controller	Parvaresh et al. (2020)	Remotely discharged within the manufacturing process	Birtel et al. (2020)	Remote control
			In servo motor	Pethig et al. (2017)	Integrated components
			In 5G architecture-enabled CPPS	Stock et al. (2021)	
Layer integration	To integrate the technical information and the business information	Pargmann et al. (2018)	In the communication layer, integrating enterprise layer (e.g. business layer) and information layer (e.g. technical layer)	Ye and Hong (2018)	Layer integration
Prediction/estimation	Wind speed	Hu et al. (2020), Li and Shen (2022)	Generation of Dynamic Simulation Model	Göllner et al. (2021)	Modelling
	The axial tension of mooring lines	Walker et al. (2021)			
	Tower load and fatigue	Branlard et al. (2020b), Branlard et al. (2020a)			
	Remaining useful life	Mehlan et al. (2022)	Track the life cycle	Marcon et al. (2019), Deuter and Imort (2021), Rauh et al. (2022)	Life cycle management

wind farm maintenance costs, unexpected shutdowns, and consequent downtimes. Predictive maintenance can be carried out with the recorded database and real-time simulation stored in the AAS of digital twins of offshore wind farms.

Parvaresh et al. (2020) established a digital twin of offshore wind turbines for the pitch angle controller pertaining to a variable wind speed control strategy for the wind turbine. Meanwhile, Birtel et al. (2020) implemented AAS in a use case where the product can be remotely discharged within the manufacturing process due to a defective product. Here, AAS is used to access and communicate all components remotely and individually, so that a component can easily control other components. For condition monitoring of offshore wind farms, the AAS can be used as an information model for interoperability among the integrated components as presented by Pethig et al. (2017) in a servo motor and by Stock et al. (2021) in 5G architecture-enabled CPPS, to increase the efficiency and flexibility.

Pargmann et al. (2018) explored digital twins to integrate not only the technical information but also the business information. Ye and Hong (2018) successfully achieved this aim by implementing AAS, referred to as RAMI 4.0, for manufacturing processes. In the enterprise layer, business data is included. The information layer consists of technical data, i.e. operation and maintenance. In the communication layer, the focus is on the integration among these layers. This proves that the implementation of AAS has the potential to realize the integration between technical and business information.

The historical data from sensors stored in AAS significantly contribute to predicting the wind speed (Hu et al. 2020; Li and Shen 2022) and the future axial tension of mooring lines (Walker et al. 2021). Branlard et al. (2020b, 2020a) presented digital twins of offshore wind farms in order to estimate the tower load and fatigue. Meanwhile, Göllner et al. (2021) generated the dynamic simulation model automatically based on the standardized and interoperable information model where all necessary data is mapped into the AAS structure. Moreover, by modelling wind turbine gear stages for digital twin, (Mehlan et al. 2022) estimate the remaining useful life (RUL) of offshore wind farms. The role of AASs in life cycle management (Marcon et al. 2019; Deuter and Imort 2020; Rauh et al. 2022) facilitates estimating the turbine states and tracking the life cycle of the physical objects. Moreover, by gaining a better understanding of the life cycle of offshore wind farms, we can analyze the shortcomings of existing turbine models, both physical and digital assets, for further improvement. The simplicity of interoperable AASs enables all stakeholders to observe and analyze the condition of the devices for improved decision-making, hence leading to increased productivity and effectiveness.

Case study

This segment provides findings from a comprehensive investigation of a previous case study conducted by one of the authors in Haghshenas et al. (2023). The case study is based on the Hywind Tampen floating wind farm project, developed by Equinor, which aimed to implement a digital twin in offshore wind farms Qaiser et al. (2023). The Hywind Tampen consists of eleven floating wind turbines, generating 94.6 megawatts of power, that was designed to meet one-third of the yearly energy demand of five oil platforms in the Norwegian North Sea. The project demonstrated a positive impact in terms of reducing the yearly emissions of 200,000 tons of CO_2 and 1000 tons of NOx from gas turbine usage (Qaiser et al. 2023).

Digital twins in the context of industry 4.0 for offshore wind farms

The previous case study established the significant potential relating to implementing a digital twin in offshore wind farms to predict bearing failures and thus enhance decision-making of scheduled maintenance. The study also successfully demonstrated the visualization of the Hywind Tampen in various formats, including a 2D Graphical User Interface (GUI) cloud, 3D, and augmented reality. In the current study, we visualize the actual weather data (such as wind speed and direction) from the Norwegian North Sea where the Hywind Tampen is located. We also specifically analyze the simulation of the data processing and the communication protocol of how data from several sources was transmitted and integrated. Finally, we present an overview of how an AAS-based digital twin could be conceptually applied in the case study.

Data source The creation of a digital twin integrates the data from a variety of sources, comprising various data types, in order to generate a virtual model capable of replicating the behavior of real-world physical assets. Once a digital twin has been established, it can be utilized to generate simulations and to forecast and assess the performance of the corresponding physical entity. Data sources that can be utilized in the construction of a digital twin may include visual data, measurement data, historical data, etc (Hasan et al. 2023). In this case study, these data sources are classified into four categories: static data, simulated data, live data, and historical data (Haghshenas et al. 2023).

Visualization The visualization of the case study was achieved through various means, namely 3D visualization, a 2G GUI cloud, and augmented reality (AR). The 3D visualization is applied in Unity 3D, an open-source platform that enables users to easily add assets from an inventory to a scene and to customize scenarios by adjusting internal and external factors. The visualization consists of wind turbines and oil rigs as the representation of the Hywind Tampen scenario, as seen in Fig. 3.

The system interface provides two modes for users: operator and editor mode. Both modes allow modification of the wind farm inventory and wind condition settings, but the editor mode provides greater control over system parameters and configurations, accessible to users with higher hierarchical levels. Users in editor mode can adjust individual turbine settings, such as blade length, turbine efficiency, and various types of losses. For both modes, users can view the power and RPM outputs of a specific turbine on gauges and line charts. The option to map the output power of each turbine is available by selecting the "map output power" feature. Additionally, users can check the "map bearing temperature" feature to view the current, maximum, and minimum temperature range of each turbine's bearing. This feature can be useful for prediction purposes, though it is not discussed in detail in this study.

The power generated by a wind turbine can be calculated using the equation:

Fig. 3 3D visualization of the Hywind Tampen floating wind farm

$$P = \frac{1}{2}\rho A V^3 Cp\mu \tag{1}$$

where P is the output power, ρ is the air density, A is the swept turbine area, V is the wind speed, Cp is the power coefficient, and μ represents various losses, including mechanical and electrical losses. This equation is used to measure the power output of a wind turbine. The visualization tool is designed to enable adjustments to not only wind speed and direction but also blade length, turbine efficiency, and losses, which impact the calculated power output.

The data sources utilized by the system are modifiable within four categories. The first category, named "Unity Data" as the static data, encompasses user-defined parameters established within Unity3D by the user and editor to outline specific scenarios and desired outcomes. Both operator and editor modes are employed in this category, where users define their scenarios by adding turbines or oil rigs and setting wind speed or direction. The second category, so-called "FMU data" as the simulated data, incorporates complex simulated models imported from Matlab Simulink via the FMI plugin (as detailed in "Simulation" segment) to perform advanced experiments within Unity3D. In the existing case study, the wind speed was set to fluctuate between 12 and 14 m/s to demonstrate the variation in the output power. Meanwhile, the present study visualizes actual weather data from the Tampen area of the Norwegian North Sea, between the Snorre and Gullfaks oil fields. Consequently, the displayed power output in the adapted case study reflects the actual generated power. The third, named "OPCUA Data," consists of the real-time sensor data being transferred from physical to digital assets through OPC UA (Kandemir et al. 2023) (as detailed in the "Communication protocol" segment). This allows for real-time data to be analyzed in "what-if" simulations for decision-making support. If the results from these "what-if" scenarios are unfavorable, digital twins can send commands to the physical assets. This mode aims to implement digital twins by providing two-way communication between physical and digital assets. The last category, referred to as the "Actual Data", encompasses historical data obtained from an actual wind farm to examine the semi-realistic scenarios.

The 2D visualization is implemented through a cloud-based GUI platform utilizing Node-RED (as detailed in "Communication protocol" segment) in order to display the live data simultaneously with 3D and AR visualizations. The 2D dashboard aims to facilitate accessibility to the visualization by other users across various computers and mobile devices, especially when changes need to be made to physical and digital assets. As depicted in Fig. 4, the 2D dashboard comprises gauges, charts, indicators, and input fields.

The previous case study presented the utilization of augmented reality technology through the implementation of the PTC Vuforia plugin within Unity3D in order to improve user interaction and capabilities. By leveraging IoT technologies, users can access digital assets through their smartphones without the need for advanced hardware. The augmented reality platform not only provides a visual display but also enables users to set wind farm conditions as well as in the 3D platform. The augmented reality platform operates in conjunction with both the 3D and 2D visualization platforms. Figure 5 provides a representation of augmented reality.

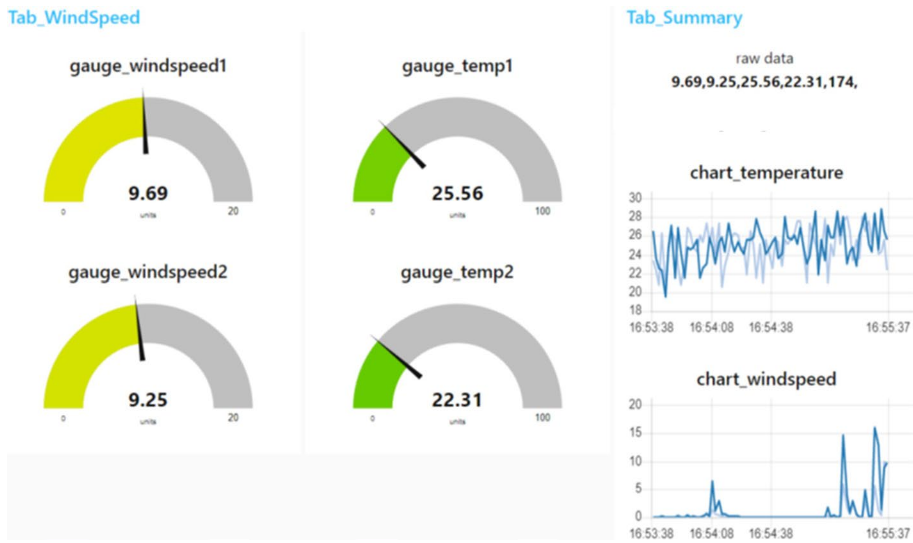

Fig. 4 2D visualization through a cloud-based GUI platform utilizing Node-RED (Haghshenas et al. 2023)

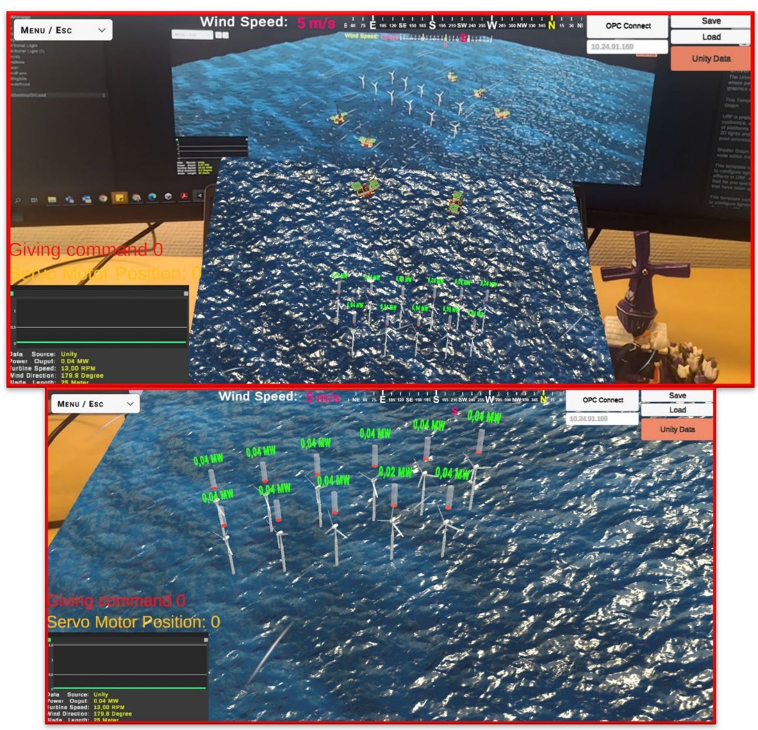

Fig. 5 Augmented reality visualization for the Hywind Tampen wind farm (below: the zoomed-in view)

Simulation The simulation segment serves as an intermediary between the data sources and the visualization segment, meaning that the simulation input is the data source, and the simulation output/result is the visualization as seen in Figs. 3, 4, and 5. It is responsible for converting raw data into internal variables that can be associated with any object (such as turbine, tower, and wind farm), and for managing the data service and data bank. In Unity3D, simulation functions process and calculate all data received from various sources using customized parameters to generate the desired output and visualize it in the scene. These functions are based on wind energy physics and dynamic system equations, and can be modified by the user to perform what-if scenarios. The parameters specified by the user (such as blade length and yaw angle) and the data received from the data sources are integrated into Unity3D functions to generate output values such as power and rotor speed, representing the condition of the wind farm based on the designed experiment or real-time data from the physical asset. Before simulating the complex dynamic behavior of the entire wind farm system, it is necessary to simulate each component using different software at the same time, a process called co-simulation (CS). The leading standard for exchanging dynamic simulation models of each simulated data is the Functional Mock-Up Interface (FMI), whose model file is the Functional Mock-up Unit (FMU). In this case study, we created the original model in Matlab, which supports the FMI standard applying FMU version 2.0 CS. This version includes a solver and supports the directional derivatives and a clarified specification (Blochwitz et al. 2012). The case study uses Unity3D to simulate static data by calculating and returning output based on user-defined data. The simulated data is imported and processed from Matlab and Simulink in the FMU file format through the FMI plugin. Live data from physical assets can be accessed by using the OPC UA protocol and Node-RED (see the Communication Protocol segment) to send real-time sensor data to Unity3D for processing and calculation. In order to create a realistic scenario of the wind farm, the historical data from CSV files are imported to Unity3D and used in the simulation functions to generate output measurements, including the artificial representation of bearing temperature and vibration for each wind turbine which can be set to change at user-defined intervals. Upon initiating Unity3D, the system begins to extract bearing temperature and vibration data from the CSV files and applies it to each turbine.

Communication protocol The communication protocol within the framework of Industry 4.0 plays a vital role in promoting connectivity among assets, facilitating seamless automatic integration (Ambarita et al. 2023). This study uses a framework that combines OPC UA and Node-RED to connect different parts of a system. The OPC UA is leveraged as the primary means of facilitating horizontal and vertical communications between subsystems in the field layer and upper-layer entities, utilizing authenticated communication to establish a connection between servers and clients. The OPC UA servers are created using the UaExpert application, with clients able to connect to the available servers from various devices. Node-RED is an open-source Application Programming Interface (API) platform developed by IBM's Emerging Technology Services team, and provides a wide range of online services for connecting physical and digital assets. All the sensor data are collected and connected to the Arduino board, which is connected to a PC via serial ports in order to transmit the measured data to the system. The collected real-time data is then transferred to Unity3D via the OPC UA protocol utilizing Node-RED. Within Node-RED, a serial port block is augmented to receive the collected data from the Arduino board and transmit it to the OPC UA client block, which is connected to the primary OPC UA server. This data can be disseminated and utilized by other OPC UA clients. Two clients are employed to facilitate data transfer among the available platforms. The first client, developed in C# within Unity3D, is utilized for communication with the 3D visualization and Augmented Reality platforms. The second client, created in Node-RED, is utilized to receive sensor data and facilitate communication with the 2D GUI dashboard. This way, the sensor data can be easily accessed through cloud platforms and WiFi devices.

Discussion: interoperable digital twin solutions for wind farm applications

The current case study holds a significant opportunity for the implementation of an interoperable digital twin using OPC UA. The literature review in "Digital twin framework in the manufacturing industry" highlights OPC UA as the recommended tool in the communication layer of RAMI4.0. The digital twin framework in the manufacturing industry leverages the interoperability of OPC UA to facilitate data exchange and provide information from diverse domains of interest. Cavalieri et al. (2019) conducted research on an OPC UA-based Asset Administration Shell by mapping the AAS metamodel into the OPC UA information model. The authors created ObjectTypes (such as AASType, AASReferenceType, SubmodelType, AssetType, and DataSpecificationType), DataTypes (such as Identifier, KeyType, and KeyElements), and ReferenceTypes (such as HasSemantic, HasConceptDescription, and IsDerivedFrom) in OPC UA to correspond with the asset, AAS Reference, AAS Identifier, AAS type and instance, AAS derivedFrom, AAS Submodel, AAS SubmodelElement, and AssetAdministrationShell in the AAS metamodel.

The OPC UA Information Model standardizes how servers communicate information to clients through the utilization of OPC UA Nodes organized within the OPC UA AddressSpace (Lee et al. 2017; Foundation 2017) where the values from sensors are read and updated (Pribiš et al. 2021). Each OPC UA Node is classified into several NodeClasses, such as Variable NodeClass and Object NodeClass. The Variable NodeClass is employed in modelling data and represents values from various sensors or from one sensor on several properties (such as temperature sensor from the gearbox, generator, hub, etc) in offshore wind turbines. To distinguish between different sources of data, OPC UA employs two main VariableTypes, namely the DataVariableType and PropertyType. The Variable NodeClass includes an attribute named Value for storing data and an attribute named DataType for specifying the content of the attribute Value. The Object NodeClass acts as a container for other OPC UA Objects and Variables. In cases where the Object Node does not possess an attribute capable of storing a data value (e.g., the temperature value of a sensor), an OPC UA DataVariable Node is employed to represent data associated with that Object. These features of OPC UA effectively specify and map abundant data from various sources in accordance with AAS types and instances. Since offshore wind farms have sensor data from various sources concerning the variability of data type, variables, values, and properties, the OPC UA Variable and Object NodeClass function potentially addresses the mapping needs of offshore wind farms.

Cavalieri and Salafia (2020a) also presented a case study on AAS modeling a motor controller. The mapping applied in their case study was founded on the proof of concept known as the AAS Information Model, which is available free of charge on Salafia (2020). The authors concluded that their approach offers the advantage of automatically integrating data without human intervention. Pribiš et al. (2021) proposed an AAS design methodology that implements an OPC UA Server at the embedded device to facilitate direct data exchange between sensors and actuators, reducing integration efforts and computational requirements.

In order to support our analysis of implementing AAS for offshore wind farms, we briefly explored the AASX Package Explorer. Using a simple example, we generated three assets (sensor, blade, and generator) for a wind farm, marked with a yellow circle in Fig. 6. Each asset is assigned an AAS that represents different turbines, marked with a green circle. We designed submodels for the AAS named SensorTurbine1 to represent

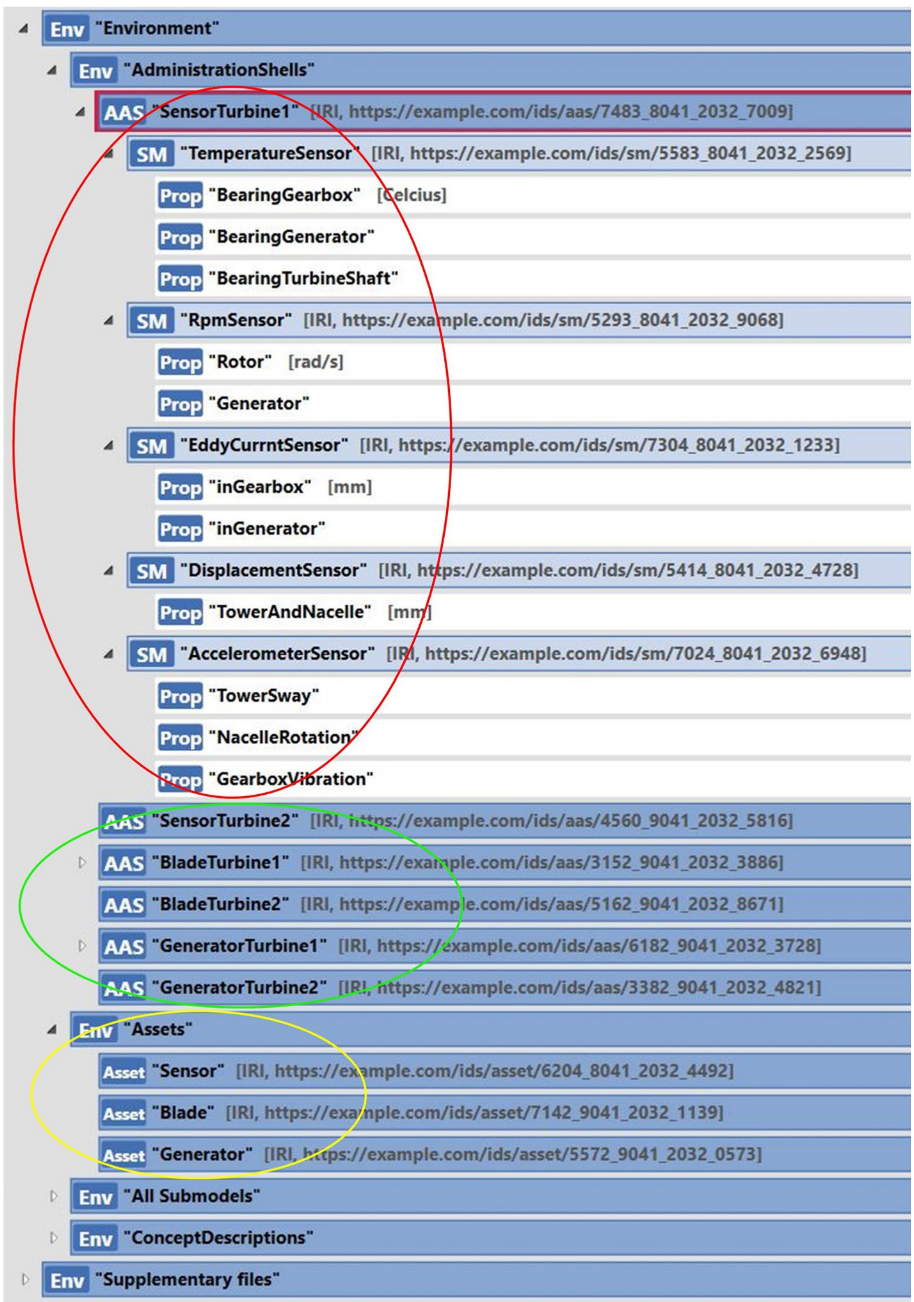

Fig. 6 A simple example of AASX Package Explorer for a wind farm

sensor variables such as temperature, RPM, eddy current, displacement, and accelerometer, marked with a red circle. To account for temperature sensors placed in various locations, we created SubmodelElements (properties) in the bearing gearbox, generator, and turbine shaft, as well as for other sensors based on the requirements. At the property level, data is categorized into three types: (i) constant, a property with a value that does not change over time, such as a coded value, (ii) parameter, a property that is set once and typically does not change over time, such as a configuration parameter, and (iii) variable, a property that is calculated during runtime. Consequently, the sensor data is classified as a variable.

In Fig. 7 as marked with a purple circle, we developed submodels for the AAS named BladeTurbine1, based on the type of data, such as design data and material. Design data are comprised of several properties including NACA type, blade length and width, angle of attack, and others. Material submodel represents information on blade material. For the AAS named GeneratorTurbine1 as marked with a black circle, we created submodels to encompass all the data we could acquire from the generator manufacturer, such as the nameplate, technical data consisting of product classification and technical properties, documentation, electric and fluid plan such as bill of material, contact information for service, and identification including the supplier information. All these properties were classified as constant. In order to simplify and standardize information, AASX Package Explorer provides a plug-in general form for several submodels, such as document, nameplate, identification, image map, and technical data. This AAS feature represents an optimal means of facilitating asset management that encompasses data specification and classification.

In order to facilitate a deeper understanding of submodels, ConceptDescriptions are created for SubmodelElements. The semantic ID of the SubmodelElement is automatically linked to the ID of the corresponding ConceptDescription. The use of a semantic ID for SubmodelElements is mandatory for an automatic system to identify and understand the meaning of the SubmodelElements, such as units or logical datatypes. The semantic ID can refer to a ConceptDescription within the AAS environment or an external repository such as IEC CDD, eClass, or a company/consortia repository. If multiple SubmodelElements share similar information, they will have a similar ConceptDescription ID attached. If Submodels and SubmodelElements were created by a company or stored in an external repository, they can be imported from dictionaries, tables, JSON, CSV files, or URLs. Several interoperability options are available to support AAS, such as importing AutomationML into AASX, importing AAS from i4aas-nodeset, importing OPC UA nodeset.xml as submodel, and reading OPC values into submodel.

Moreover, there are events between the AASX Package Explorer and the AASXServer where the time series data are being collected and simulated. It could be the simulated JSON data, OPC UA, or OPC UA together with the AASXServer. Whenever plenty of samples are collected, new collections will be created. Through this server, data from OPC UA is connected to the package explorer by copying the REST IP of the server into the AASX Package Explorer. There is also a feature in the package explorer to order "stay connected", thus in the package explorer, we receive live data from the server. It shows that all available menus in AASX Package Explorer contribute to the use of AAS for achieving interoperability as an Industry 4.0 standard.

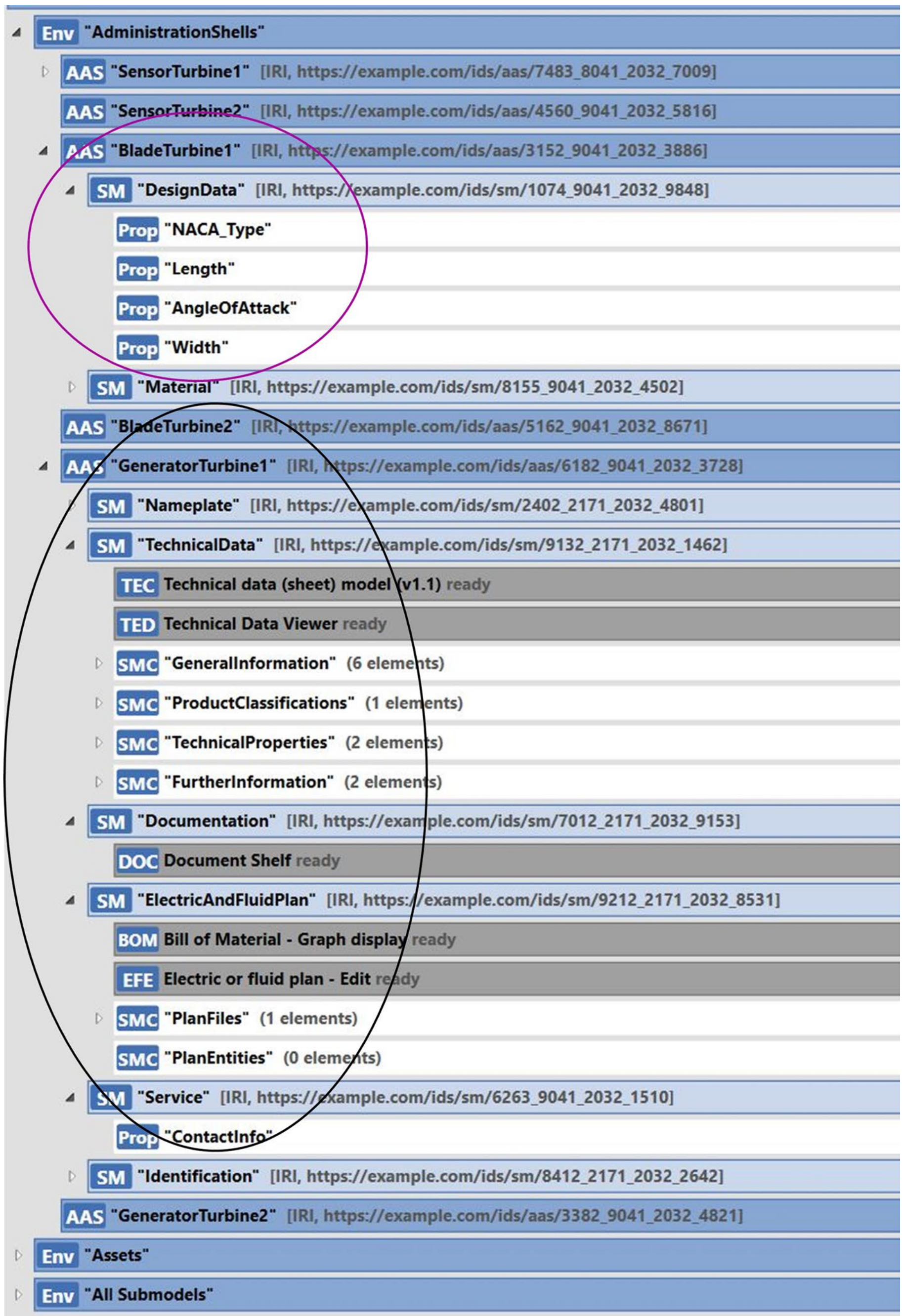

Fig. 7 Submodels of blade and generator

Conclusion

Being part of a broader study aiming for the improvement of digital twins in offshore wind farms, this paper set out to provide insights into and map the potential related to transferring the knowledge of interoperable digital twins from the manufacturing industry. Using a qualitative approach, we established a research approach consisting of three phases, where each phase provided findings that led us to the next phase. Through a comprehensive literature study on the implementation of digital twins in offshore wind farms, we discovered that the frameworks applied in offshore wind farms were insufficient in achieving interoperability. Meanwhile, in the manufacturing industry, Asset Administration Shell (ASS) has been promoted as a promising framework for implementing digital twins in the standardized Industry 4.0 to perform interoperability. Through the case study and our investigation on the AASX Package Explorer, we concluded that implementing AAS should be a possible development to further improve digital twins in offshore wind farms, thereby achieving interoperability under Industry 4.0 standards.

We are, however, aware that this study only presents interoperable digital twins in offshore wind farms conceptually. To bridge the gap between theory and practice, future studies should contribute to practically implementing AAS-based digital twins in offshore wind farms. Moreover, close collaboration among significant parties is highly recommended. This implies providing data from the project owner, open-source implementation of AAS (Jacoby et al. 2023), and tools with flexible architecture as offered by FA^{3}ST (Stojanovic et al. 2021). Through close collaboration, future studies initiate the application of AAS type 1 for modelling purposes and subsequently progress to AAS type 2. This progression involves utilizing AAS type 2 for tasks such as condition monitoring, control, and predictive maintenance concerning time-series data. Implementing a practical AAS-based digital twin in offshore wind farms should be a desired and possible development to realize energy industry 4.0 where all assets and stakeholders can seamlessly connect and integrate without human intervention, resulting in improved decision-making and enhanced productivity.

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Availability of data and materials
Data sharing does not apply to this article as no datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable

Consent for publication
Not applicable

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI in scientific writing
During the preparation of this work, the author(s) used ChatGPT-3.5 in order to rephrase the writing style. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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References

Ambarita EE, Karlsen A, Osen O et al (2023) Towards fully autonomous floating offshore wind farm operation & maintenance. Energy Rep. 9:103–108 (The 8th international conference on sustainable and renewable energy engineering)
Augustyn D, Ulriksen MD, Sørensen JD (2021) Reliability updating of offshore wind substructures by use of digital twin information. Energies 14(18):5859
Birtel M, Motsch W, Popper J et al (2020) Method for the development of an asset administration shell in a product-driven modular production—realizing an active digital object memory. In: Proceedings of 2020 IEEE conference on industrial cyberphysical systems (ICPS), pp 583–588
Blochwitz T, Otter M, Akesson J et al (2012) Functional mockup interface 2.0: the standard for tool independent exchange of simulation models. In: 9th international modelica conference
Branlard E, Giardina D, Dana S et al (2020a) Augmented Kalman filter with a reduced mechanical model to estimate tower loads on a land-based wind turbine: a step towards digital-twin simulations. Wind Energy Sci 5(3):1155–1167
Branlard E, Jonkman J, Dana S et al (2020b) A digital twin based on OpenFAST linearizations for real-time load and fatigue estimation of land-based turbines. J Phys Conf Ser 1618(2):022030
Casado MG, Eichelberger H (2021) Industry 4.0 resource monitoring—experiences with micrometer and asset administration shells. In: Symposium on software performance. Zenodo
Cavalieri S, Salafia MG (2020a) Insights into mapping solutions based on OPC UA information model applied to the industry 4.0 asset administration shell. Computers 9(2):28
Cavalieri S, Salafia MG (2020b) A model for predictive maintenance based on asset administration shell. Sensors 20(21):6028
Cavalieri S, Mulé S, Salafia MG (2019) OPC UA-based asset administration shell. In: IECON 2019—45th annual conference of the IEEE industrial electronics society, pp 2982–2989
Chen X, Eder MA, Shihavuddin A et al (2021) A human-cyber-physical system toward intelligent wind turbine operation and maintenance. Sustainability 13(2):561
Chetan M, Yao S, Griffith DT (2021) Multi-fidelity digital twin structural model for a sub-scale downwind wind turbine rotor blade. Wind Energy 24(12):1368–1387
Cooper JP, Jackson S, Kamojjala S et al (2022) Demystifying digital twins: definitions, applications, and benefits. J Am Water Works Assoc 114(5):58–65
Demiris G, Oliver DP, Washington KT (2019) Chapter 3—Defining and analyzing the problem. In: Demiris G, Oliver DP, Washington KT (eds) Behavioral intervention research in hospice and palliative care. Academic Press, Oxford, pp 27–39
Deuter A, Imort S (2020) PLM/ALM integration with the asset administration shell. Procedia Manuf 52:234–240 (System-integrated intelligence—intelligent, flexible and connected systems in products and production proceedings of the 5th international conference on system-integrated intelligence (SysInt 2020), Bremen, Germany)
Deuter A, Imort S (2021) Product lifecycle management with the asset administration shell. Computers 10(7):84
di Orio G, Maló P, Barata J (2019) NOVAAS: a reference implementation of Industrie4.0 asset administration shell with best-of-breed practices from it engineering. In: Proceedings of IECON 2019—45th annual conference of the IEEE industrial electronics society, pp 5505–5512
Ding K, Fan L, Liu C (2021) Manufacturing system under I4.0 workshop based on blockchain: research on architecture, operation mechanism and key technologies. Comput Ind Eng 161:107672
Ebrahimi A (2019) Challenges of developing a digital twin model of renewable energy generators. In: IEEE 28th international symposium on industrial electronics (ISIE), pp 1059–1066
Fahim M, Sharma V, Cao TV et al (2022) Machine learning-based digital twin for predictive modeling in wind turbines. IEEE Access 10:14184–14194
Foundation O (2017) OPC UA part 3—address space model. OPC Foundation
Geschäftsstelle (2018) Detail of the asset administration shell—part 1. Plattform Industrie 4.0
Grosse CU (2019) Monitoring and inspection techniques supporting a digital twin concept in civil engineering. In: Fifth international conference on sustainable construction materials and technologies
Göllner D, Pawlik T, Schulte T (2021) Utilization of the asset administration shell for the generation of dynamic simulation models. In: Proceedings of 2021 IEEE international conference on industrial engineering and engineering management (IEEM), pp 808–812
Haghshenas A, Hasan A, Osen O et al (2023) Predictive digital twin for offshore wind farms. Energy Inform 6(1):1–26
Hasan A, Hu Z, Haghshenas A et al (2023) An interactive digital twin platform for offshore wind farms' development. Springer Nature, Singapore, pp 269–281
Herzog R, von Riegen S, Hotz L (2020) Towards a comprehensive architecture for autonomous adaptive machines. In: Proceedings of 2020 25th IEEE international conference on emerging technologies and factory automation (ETFA), pp 1073–1076
Hu W, He Y, Liu Z et al (2020) A hybrid wind speed prediction approach based on ensemble empirical mode decomposition and BO-LSTM neural networks for digital twin. In: ASME power conference 2020, vol 83747. ASME, p v001T08A009
Iosifidis N, Zhong Y, Hu B et al (2021) Reliability of wind turbine power modules using high-resolution wind data reconstruction: a digital twin concept. In: Proceedings of 2021 IEEE energy conversion congress and exposition (ECCE), pp 3630–3637
Iñigo MA, Porto A, Kremer B et al (2020) Towards an asset administration shell scenario: a use case for interoperability and standardization in industry 4.0. In: Proceedings of NOMS 2020–2020 IEEE/IFIP network operations and management symposium, pp 1–6
Jacoby M, Baumann M, Bischoff T et al (2023) Open-source implementations of the reactive asset administration shell: a survey. Sensors 23(11):5229
Kandemir E, Liu J, Hasan A (2023) Digital twin-driven dynamic repositioning of floating offshore wind farms. Energy Rep 9:208–214 (Proceedings of 2022 7th international conference on renewable energy and conservation)

Lang D, Grunau S, Wisniewski L et al (2019) Utilization of the asset administration shell to support humans during the maintenance process. In: Proceedings of 2019 IEEE 17th international conference on industrial informatics (INDIN), pp 768–773
LeBlanc B, Ferreira C (2020) Experimental characterization of H-VAWT turbine for development of a digital twin. J Phys Conf Ser 1452(1):012057
Lee B, Kim DK, Yang H et al (2017) Model transformation between OPC UA and UML. Comput Stand Interfaces 50:236–250
Lee J, Zhao F, Dutton A et al (2021) GWEC global wind report 2021. In: Global wind report. www.gwec.net
Li F, Li L, Peng Y (2021) Research on digital twin and collaborative cloud and edge computing applied in operations and maintenance in wind turbines of wind power farm. In: Proceedings of the 2nd international conference on green energy, environment and sustainable development (GEESD2021)
Li Y, Shen X (2022) A novel wind speed-sensing methodology for wind turbines based on digital twin technology. IEEE Trans Instrum Meas 71:1–13
Lu Q, Li X, Li G et al (2021) A general asset administration shell platform for production line design. In: Proceedings of 2021 IEEE 1st international conference on digital twins and parallel intelligence (DTPI), pp 192–195
Lüder A, Behnert AK, Rinker F et al (2020) Generating industry 4.0 asset administration shells with data from engineering data logistics. In: Proceedings of 2020 25th IEEE international conference on emerging technologies and factory automation (ETFA), pp 867–874
Marcon P, Arm J, Benesl T et al (2019) New approaches to implementing the SmartJacket into industry 4.0. Sensors 19(7):1592
Mehlan FC, Pedersen E, Nejad AR (2022) Modelling of wind turbine gear stages for digital twin and real-time virtual sensing using bond graphs. J Phys Conf Ser 2265(3):032065
Moghadam FK, de Rebouças GFS, Nejad AR (2021) Digital twin modelling for predictive maintenance of gearboxes in floating offshore wind turbine drivetrains. Forschung im Ingenieurwesen 85:273–286
Momber AW, Möller T, Langenkämper D et al (2022) A digital twin concept for the prescriptive maintenance of protective coating systems on wind turbine structures. Wind Eng 46(3):949–971
Montoya B, Naranjo-Riofrío C, López-Estrada L et al (2022) Development of a wind turbine digital-twin for failure prognosis: first results. In: Proceedings of 2022 5th international conference on advanced systems and emergent technologies (IC ASET), pp 29–33
Motsch W, Sidorenko A, David A et al (2021) Electrical energy consumption interface in modular skill-based production systems with the asset administration shell. Procedia Manuf 55:535–542
Oneto L, Coraddu A, Cipollini F et al (2018) Crash stop maneuvering performance prediction: a data-driven solution for safety and collision avoidance. Data-Enabled Discov Appl 2:1–11
Oñederra O, Asensio FJ, Eguia P et al (2019) MV cable modeling for application in the digital twin of a windfarm. In: Proceedings of 2019 international conference on clean electrical power (ICCEP), pp 617–622
Panda SK, Schröder T, Wisniewski L et al (2018) Plug & produce integration of components into OPC UA based data-space. In: Proceedings of 2018 IEEE 23rd international conference on emerging technologies and factory automation (ETFA), pp 1095–1100
Pargmann H, Euhausen D, Faber R (2018) Intelligent big data processing for wind farm monitoring and analysis based on cloud-technologies and digital twins: a quantitative approach. In: Proceedings of 2018 IEEE 3rd international conference on cloud computing and big data analysis (ICCCBDA), pp 233–237
Parvaresh A, Abrazeh S, Mohseni SR et al (2020) A novel deep learning backstepping controller-based digital twins technology for pitch angle control of variable speed wind turbine. Designs 4(2):15
Pethig F, Niggemann O, Walter A (2017) Towards Industrie 4.0 compliant configuration of condition monitoring services. In: Proceedings of 2017 IEEE 15th international conference on industrial informatics (INDIN), pp 271–276
Pribiš R, Beňo L, Drahoš P (2021) Asset administration shell design methodology using embedded OPC unified architecture server. Electronics 10(20):28
Qaiser MT, Ejaz J, Osen O et al (2023) Digital twin-driven energy modeling of Hywind Tampen floating wind farm. Energy Rep 9:284–289 (Proceedings of 2022 7th international conference on renewable energy and conservation)
Rasheed A, San O, Kvamsdal T (2020) Digital twin: values, challenges and enablers from a modeling perspective. IEEE Access 8:21980–22012
Rauh L, Gärtner S, Brandt D et al (2022) Towards AI lifecycle management in manufacturing using the asset administration shell (AAS). Procedia CIRP 107:576–581 (Leading manufacturing systems transformation—proceedings of the 55th CIRP conference on manufacturing systems 2022)
Redeker M, Volgmann S, Pethig F et al (2020) Towards data sovereignty of asset administration shells across value added chains. In: Proceedings of 2020 25th IEEE international conference on emerging technologies and factory automation (ETFA), pp 1151–1154
Rehman HU, Chaplin JC, Zarzycki L et al (2022) Service based approach to asset administration shell for controlling testing processes in manufacturing. IFAC-PapersOnLine 55(10):1852–1857 (10th IFAC conference on manufacturing modelling, management and control MIM 2022)
Sahoo AK, Majumder U, Nielsen MW et al (2017) Strength of shear web with circular hole in wind turbine blades and using digital twining concept to reduce material testing. In: Proceedings of ASME 2017 gas turbine India conference, vol 2, p v002T06A005
Sakurada L, Leitao P, De la Prieta F (2021) Towards the digitization using asset administration shells. In: Proceedings of IECON 2021—47th annual conference of the IEEE industrial electronics society, pp 1–6
Salafia M (2020) Coreaas. In: https://github.com/OPCUAUniCT/coreAAS by a research group at the University of Catania, Department of Electrical Electronic and Computer Engineering
Salimbeni S, Andaloro G, Redchuk A (2022) Digital twin for the management of wind power plants. In: SINTEF
Seif A, Toro C, Akhtar H (2019) Implementing industry 4.0 asset administrative shells in mini factories. Procedia Comput Sci 159:495–504 (Knowledge-based and intelligent information & engineering systems: proceedings of the 23rd international conference KES2019)

Sivalingam K, Sepulveda M, Spring M et al (2018) A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. In: Proceeding of 2018 2nd international conference on green energy and applications (ICGEA), pp 197–204
Sjarov M, Lechler T, Fuchs J et al (2020) The digital twin concept in industry—a review and systematization. In: 2020 25th IEEE international conference on emerging technologies and factory automation (ETFA), vol 1. IEEE, pp 1789–1796
Stock D, Schneider M, Bauernhansl T (2021) Towards asset administration shell-based resource virtualization in 5G architecture-enabled cyber-physical production systems. Procedia CIRP 104:945–950 (54th CIRP CMS 2021—towards digitalized manufacturing 4.0)
Stojanovic L, Usländer T, Volz F et al (2021) Methodology and tools for digital twin management-the FA3ST approach. IoT 2(4):717–740
Stump J (2020) Offshore industry embraces digital twin technology. In: https://www.offshore-mag.com/production/article/14185502/offshore-industry-embraces-digital-twin-technology. Accessed Dec 5 2021
Tantik E, Anderl R (2017) Integrated data model and structure for the asset administration shell in Industrie 4.0. Procedia CIRP 60:86–91 (Complex systems engineering and development proceedings of the 27th CIRP design conference Cranfield University, UK 10th–12th May 2017)
Trueba AP, Fernández J, Garrido-Mendoza CA et al (2021) A concept for floating offshore wind mooring system integrity management based on monitoring, digital twin and control technologies. In: International conference on offshore mechanics and arctic engineering, vol 9. Ocean Renewable Energy. ASME, p v009T09A019
Tygesen UT, Jepsen MS, Vestermark J et al (2018) The true digital twin concept for fatigue re-assessment of marine structures. In: Proceedings of ASME 2018 37th international conference on offshore mechanics and arctic engineering, p v001T01A021
Valk HVD, Haße H, Möller F et al (2020) A taxonomy of digital twins. In: Proceeding of 26th Americas conference on information systems (AMCIS). https://publica.fraunhofer.de/handle/publica/412359
Verdouw C, Tekinerdogan B, Beulens A et al (2021) Digital twins in smart farming. Agric Syst 189:103046
Wadhwani M, Deshmukh S, Dhiman HS (2022) Digital twin framework for time to failure forecasting of wind turbine gearbox: a concept. Cornell University. https://arxiv.org/abs/2205.03513
Walker J, Coraddu A, Collu M et al (2021) Digital twins of the mooring line tension for floating offshore wind turbines to improve monitoring, lifespan, and safety. J Ocean Eng Mar Energy 8:1–16
Walter J, Grau S, Raczok T et al (2022) Bringing the new class of cable-driven parallel robots to the world of industrial cyber-physical systems based on RAMI 4.0. In: Proceedings of 2022 IEEE 5th international conference on industrial cyber-physical systems (ICPS), pp 1–6
Wang M, Wang C, Hnydiuk-Stefan A et al (2021) Recent progress on reliability analysis of offshore wind turbine support structures considering digital twin solutions. Ocean Eng 232:109168
Xiangjun Z, Ming Y, Xianglong Y et al (2020) Anomaly detection of wind turbine gearbox based on digital twin drive. In: Proceedings of 2020 IEEE 3rd student conference on electrical machines and systems (SCEMS), pp 184–188
Xu X, Lu Y, Vogel-Heuser B et al (2021) Industry 4.0 and industry 5.0-inception, conception and perception. J Manuf Syst 61:530–535
Ye X, Hong SH (2018) An automationml/OPC UA-based industry 4.0 solution for a manufacturing system. In: Proceedings of 2018 IEEE 23rd international conference on emerging technologies and factory automation (ETFA), pp 543–550
Ye X, Hong S, Song W et al (2021) An industry 4.0 asset administration shell-enabled digital solution for robot-based manufacturing systems. IEEE Access 9:1–11
Zeitouni MJ, Parvaresh A, Abrazeh S et al (2020) Digital twins-assisted design of next-generation advanced controllers for power systems and electronics: wind turbine as a case study. Inventions 5(2):19
Zhao H, Hu W, Liu Z et al (2021) A CapsNet-based fault diagnosis method for a digital twin of a wind turbine gearbox. In: Proceedings of ASME 2021 power conference, ASME power conference. ASME, p v001T09A016

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