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Joint Best Practices for Classifying and Valuing Digital Twins in Wind Energy

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Executive Summary

In wind energy, digital twins have the potential to maximise the value of data by providing real-time monitoring of physical systems, integrating predictive models, enabling autonomous operations and creating actionable insights. However, digital twins remain a nebulous concept, and the expression “digital twin” is applied to an enormous range of implementations at different maturity and complexity levels. This makes it difficult to understand and quantify their value, and ultimately to make investment decisions that weigh up potential complexity and value. Properly classifying and quantifying the value of digital twins in wind energy is essential for investment justification, forecasting and maintenance strategy development, standardisation, and policy alignment.

The purpose of this document is to provide practitioners in the wind energy sector with guidance for classifying and valuing digital twins. This will help them make investment decisions that weigh up the potential complexity and value of a given digital twin implementation. In this document, after the introduction the Best Practice Recommendations that are presented throughout the rest of the document are summarised. A digital twin classification scheme based on existing classifications from the literature is then suggested, and a table of high-potential wind energy digital twin use cases is presented, alongside a suggestion of how each of these use cases could be classified. Finally, a “System functionality value matrix template” for assessing the potential complexity and value of different functional capabilities of wind energy digital twins for a particular activity is introduced, together with an example application.

In this document, we understand a digital twin to mean the following [11] (see Best Practice Recommendation BPR2 below for a more detailed explanation):

“A digital twin model is a conceptual model that consists of three main elements: an actual or intended physical element that currently exists or will exist in the physical world (the “Physical Twin”), the virtual or digital counterpart that exists in the virtual or digital world (“the Digital Twin”), and the communication channel of data and information between these two elements (the “Digital Thread”). The digital twin model relies on two fundamental and necessary principles: duality and strong similarity.”

The document is a result of a collaboration between IEA Wind Task 43 and the European Academy of Wind Energy.

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1. Introduction

As Artificial Intelligence (AI) and cloud technologies advance, digital twins are gaining prominence in the energy sector as tools for improving efficiency and enabling sustainable transformation [1]. Major industry players have already made significant investments in digital twin technology for power and utilities [2], including wind energy, underscoring the growing market traction [3]. In wind energy, digital twins have the potential to maximise the value of data by providing real-time monitoring of physical systems, integrating predictive models, enabling autonomous operations and creating actionable insights [4].

However, digital twins remain a nebulous concept, and the expression “digital twin” is applied to an enormous range of implementations at different maturity and complexity levels [5]. The complex, long-term benefits of digital twins, the uncertainty in data quality, the high up-front costs, the lack of standardised metrics, the dynamic technology landscape, and the difficulty of separating the impact of the digital twin from other concurrent improvements contribute to this challenge [5, 6]. This makes it difficult to understand and quantify their value, and ultimately to make investment decisions that weigh up potential complexity and value. Quantifying the value of digital twins in wind energy is essential for investment justification, forecasting and maintenance strategy development, standardisation, and policy alignment.

Some guidance on defining, classifying and valuing digital twins already exists. For example, the AIAA and AIA Position Paper “Digital Twin: Definition & Value” aims to provide the aerospace industry perspectives on digital twins and their benefits and rationale to accelerate digital transformation [9], and the US Department of Defence provides a handbook on digital engineering and modelling practice [10], and there are a number of studies and recommendations defining what digital twins are and how they should be described [8-13]. However, the definitions differ in their specificity, and the guidance is very dependent on the particular use case. Therefore, the aim of this present work is to provide practitioners in the wind energy sector with suggestions for classifying and valuing digital twins, based on the knowledge and experience from other sectors. This will help them make investment decisions that weigh up the potential complexity and value of a given digital twin implementation. In Section 2, the Best Practice Recommendations are summarised, and in Section 3, a digital twin classification scheme based on existing classifications from the literature is presented. Section 4 introduces a table of high-potential digital twin use cases with suggestions of how each of these use cases could be classified. In Section 5, a “System functionality value matrix template” for assessing the potential complexity and value of different functional capabilities of wind energy digital twins for a particular activity is presented, together with an example application.

The document is a result of a collaboration between IEA Wind Task 43 on Digitalisation in Wind Energy and the European Academy of Wind Energy. It was developed in the following steps (as summarised in Figure 1):

Step 1: Review of the types of digital twins that have been developed so far in the wind energy domain
This review was done as part of a wider study reported in Section 6.4 of [5], in which a systematic review was done by searching the Scopus database using the query ((“decision support system” OR “expert system” OR “digital twin”) AND (“wind energy” OR “wind turbine” OR “wind plant” OR “wind power plant”)). This yielded 532 results on 1 August 2023. After checking and removing the papers that did not actually relate to any of the queried topics, and selecting the results relevant to the question posed, the remaining 181 results were compiled and classified based on the modelled component or assembly, as well as the functional level of the digital twin system. This gave us the required background knowledge and understanding of

digital twins in the wind energy domain.

Step 2: Documentation of the challenges related to building digital twins in the wind energy sector
For this, the IEA Wind Task 43 digital twin sub-group T1.4 invited twelve experts in the field who had built and implemented different digital twins to speak at monthly meetings, ranging from a digital twin architecture for rotor blade aerodynamic modelling, to digital twins of offshore structures, to a near real-time digital twin of the OpenFAST[1] software and a reduced-order model of a wind turbine based on a Kalman filter to augment high-frequency data with virtual sensing. The answers to the following questions were systematically recorded and summarised by the team in a tabular format:

- What did they build, test or do?
- What tasks did they carry out?
- What challenges did they have?
- How did they or will they solve these challenges?
- What tools did they use?
- What would they recommend to someone else doing the same task(s)?

Step 3: Analysis of the findings from steps 1 and 2 and identification of the main challenges
The team manually analysed the structured findings in tabular format from step 2, together with the outcomes of step 1, in several one-hour online meetings. The following common challenges were then identified to be:

- When wind energy digital twins are referred to in reports or papers, the specific definition, type or classification of digital twin is not referred to consistently or using existing digital twin classification systems.
- The value of digital twins in wind energy is not clear, because the value can be dependent on the specific definition, type or classification of digital twin, as well as on the specific application or use case.

Step 4: Development and publication of a classification scheme that can be referred to by wind energy experts when developing or describing a digital twin
This was done through an iterative process in the IEA Wind Task 43 team, using principles from the “IEA Wind Task 43 draft Recommended Practice: Ontology creation, publication, and maintenance for wind energy domain experts [7]”, and using existing classifications. A WeDoWind space[2] was created for its further discussion and development [21], and it was published on the TechnoPortal, an ontology publishing portal [13].

Step 5: Summary of high-impact digital twin use cases using the results of steps 1 and 2
As well as using the results of steps 1 and 2 to define the key challenges, they were also used to create a list of high-impact digital twin use cases. This was also done iteratively in the group, by first making a suggestion using the results of the literature review, and adding and refining as required [22]. The list is designed to be further developed via the WeDoWind space [21].

Step 6: Definition of a process for helping organisations with their digital twin investment decisions
This was done during about six months by meeting once a month to discuss different real decision processes being carried out by members of the team and then by working together through one concrete use case. It resulted in the creation of a system functionality value matrix

[1] https://www.nlr.gov/wind/nwtc/openfast
[2] An open innovation platform and non-profit organisation: https://www.wedowind.ch/

template.

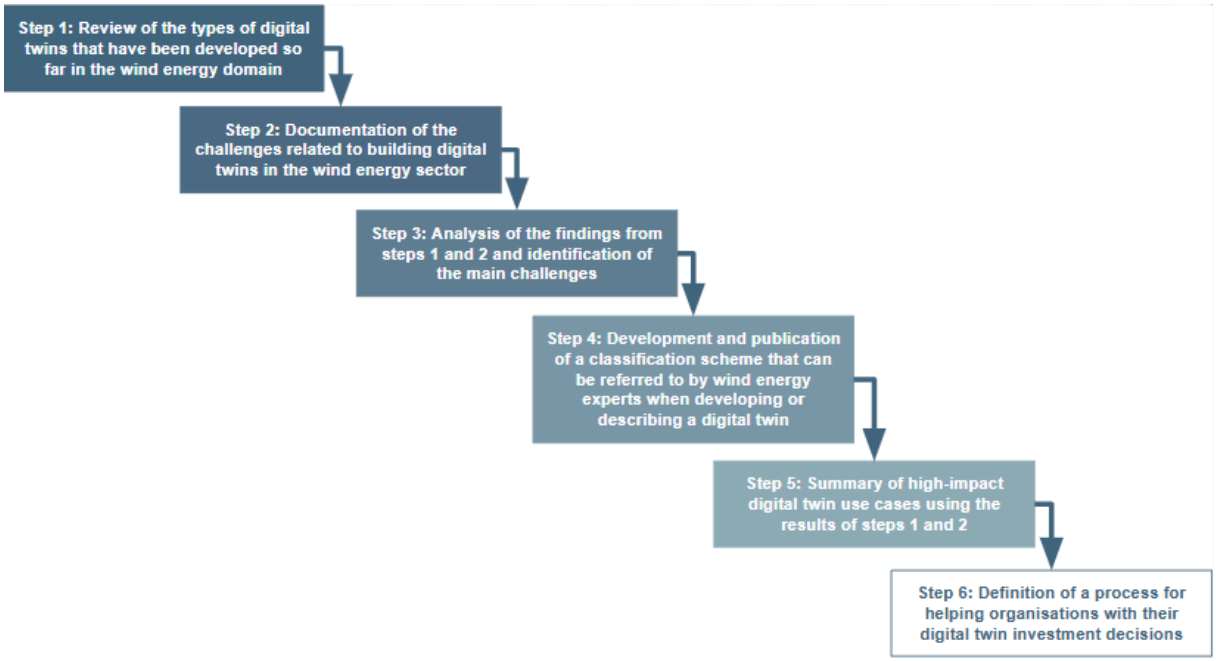

Figure 1. Overview of the steps undertaken in this work.

2. Summary of Best Practice Recommendations

The Best Practice Recommendations that are introduced in the remainder of this document are summarised in Figure 2 below for easy reference.



Figure 2. Summary of the Best Practice Recommendations.

3. Digital Twin Classification

This section relates to the development of a digital twin classification scheme in Step 4 as introduced in Section 1. Our analysis of the challenges of people in the sector building digital twins in Step 2 of this work showed that using the catch-all phrase “digital twin” to mean anything ranging from a simple simulation or measurement campaign to a fully automated decision support tool can risk devaluing the technology. Therefore, the following is recommended to wind energy practitioners:

BPR1: Always refer to a specific definition of a digital twin when describing your work, in order to convey clarity about its application and capabilities.

There are various definitions and understandings of what digital twins are, such as [8], [9], [10], [11] and [12] (summarised in [13]). These definitions differ in their specificity, ranging from a very broad definition that does not even require a physical model to be present (“A virtual representation designed to either represent updates of and send updates to a physical asset or provide a model for how such a physical asset can be created”), to a definition requiring continuous updating of real-time data, a definition requiring a bi-directional interaction between the virtual and the physical system, and a very specific definition describing details of the functionalities of the digital twin components and the expected results. The results of our analyses in stage 1 and stage 2 of this work showed that a very broad definition may risk any type of model falling under that definition of a digital twin, including a simple simulation. However, a very specific definition may risk limiting their application and usefulness in a given sector. Therefore, the following is recommended to wind energy practitioners (definition from [11]):

BPR2: Use the following digital twin model definition: “A digital twin model is a conceptual model that consists of three main elements: an actual or intended physical element that currently exists or will exist in the physical world (the “Physical Twin”), the virtual or digital counterpart that exists in the virtual or digital world (“the Digital Twin”), and the communication channel of data and information between these two elements (the “Digital Thread”). The digital twin model relies on two fundamental and necessary principles: duality and strong similarity.”

The duality principle [11] states that the conceptual model explicitly represents two distinct but related entities which coexist as counterparts of the same system: an actual or intended physical system and its corresponding digital representation. The strong similarity principle [11] requires that the digital representation maintains a sufficiently close correspondence (via the communication channel) with the physical system in terms of structure, behaviour, state, and temporal evolution. Based on the argument from [11], the twin metaphor has only two key attributes: duality and strong similarity, and therefore these two principles are sufficient to define a digital twin model. Other aspects, such as fidelity, scale, update frequency, or degree of coupling (as defined on the next page), do not define the model itself but instead characterise specific implementations and classes of digital twin models. Therefore, the following is recommended to wind energy practitioners:

BPR3: Define the type of digital twin using an appropriate classification system developed by domain experts.

This allows to differentiate between different dimensionalities, such as the connection system automation types, model fidelities, physical system lifetime stages and system functionalities. For this, the following is recommended to wind energy practitioners (from [14]):

BPR4: Use the Digital Twins Taxonomy (DITTA) to define the type of digital twin.

DITTA is a lightweight, Simple Knowledge Organisation System (SKOS)-based taxonomy that describes components of a digital twin conceptual model and classifies digital twins based on the characteristics of these components. It was developed by the IEA Wind Task 43 working group for the purpose of this document. **It is not introducing any new definitions, but it combines existing digital twin definitions to most effectively describe digital twins for wind energy activities.** It also includes several options for classification, depending on the needs of the user. DITTA was developed through an iterative process using principles from the "IEA Wind Task 43 draft Recommended Practice: Ontology creation, publication, and maintenance for wind energy domain experts [7]". **It is not intended as a finished taxonomy, but is under development.**

An overview of the DITTA is shown in Figure 3, and the full version can be accessed on the ontology publishing portal "TechnoPortal" [14]. The DITTA ontology formalises digital twins as multi-component constructs defined by both their structural composition and their typological differentiation. At the conceptual level, a digital twin is represented as the combination of three fundamental systems: the **physical system**, denoting the real-world artefact or process; the **digital system**, embodying its virtual or computational counterpart; and the **connection system**, which operationalises the digital thread through bidirectional data and information exchange. The digital system is further decomposed into three subsystems: the **data system**, which acquires, stores, and organises sensor and operational information; the **model system**, which comprises behavioural, geometric, physical, and rule-based models; and the **service system**, which performs data transformation, maintaining the synchronisation between states of a physical system and their representations in the model system. Additionally, the **service system** exposes analytical and decision-support functionalities to users and external applications. In parallel, the taxonomy establishes a taxonomy of **digital twin types** along five dimensions (note that it is not the intention of this document to suggest these evolving definitions as the absolute truth, but instead as a basis for collaborating and working on the definitions in the future):

- *Conceptual model dimensionality* refers to the number of dimensions used to describe a digital twin model [14], whereby 3D refers to digital twins with a connection system, digital system, and a physical system and 5D model distinguishes between "model", "service", and "data systems" in place of the digital system. The dimensionality can be used to guide the design of a digital twin. This distinction is purely ontological and does not prescribe specific technologies or implementations; rather, it provides a conceptual framework for categorising and comparing digital twin models according to their structural complexity and the types of entities they integrate. The role of these dimensional distinctions is to make explicit the different conceptual commitments behind various digital definitions and to support clearer communication, reuse, and interoperability of digital twin models across applications and domains.

- *Connection system automation* is a classification based on connection system automation levels [15], where “Manually coupled” is a digital representation of an existing or planned physical object that does not use any form of automated data exchange between the physical object and the digital object, i.e. the data exchange is done in a manual way, “Digital shadow” or “one-way coupled” means that an automated one-way data flow exists between the state of an existing physical object and a digital object, and “Fully coupled“ means that the data flows between a physical object and a digital object are fully integrated in both directions.
- *Model fidelity* refers to the degree to which a model represents reality:
    - “Low fidelity” means that the model systems have a high level of abstraction (e.g. coarse geometry and/or simplified behaviour), representing a limited subset of parameters/states with approximate relationships, typically intended for qualitative insight, basic monitoring, visualisation, and early development/testing.
    - “Medium fidelity” means that the model systems capture the dominant structure and behaviors needed for the target decisions, using a moderate number of parameters and moderate resolution, often combines first-principles or reduced-order models with operational data to achieve usable quantitative accuracy within a defined operating envelope, while keeping computational and data requirements manageable.
    - “High fidelity” means that the model systems capture the physical system’s relevant characteristics and behaviour with high precision, using detailed parameterisation, high-resolution state representation, and often multi-physics and probabilistic modeling, typically calibrated/validated against observations and supports quantitative prediction, optimisation, and, in some contexts, closed-loop decision support.
    - “Multi-fidelity” means that the model system employs two or more linked models (or model components) at different fidelity levels such that the twin can switch between, combine, or adaptively refine fidelity to meet the needs of specific decisions under constraints like accuracy, latency, and computational/data cost.
- *Lifecycle stage* refers to types associated with the different phases of the product lifecycle [11], where “Digital Twin Aggregate” refers to the aggregation of all the digital twin instances or all the products that have been built, “Digital Twin Instance” refers to the individual products themselves or all the products that are built, and “Digital Twin Prototype” refers to a prototypical product with variants or all the products that can be built, i.e. the prototypical physical artefact.
- S*ystem functionality* is a classification based on system functional capability [17]:
    - “Supervisory” means that data from measurements is simply ingested and stored.
    - “Operational” means that analysis of the operational data is undertaken in order to support operational decisions.
    - “Simulation/Prediction” means that models, simulations, validation, and verification and uncertainty quantification enhance the measurements, to graphical interpretation of the physical twin can be visualised, and predictions to support design or operational decisions are carried out.
    - “Intelligent/Learning” adds the ability to learn from data (via machine learning), and also adds increased levels of decision support and scenario planning.
    - “Autonomous/Management” adds the ability to carry out all decision-making (within prescribed parameters) and manage the asset concerned with minimal human intervention.
- The taxonomy includes alternative system functionality schemes, which are similar, including classification according to [18] (Standalone; Descriptive; Diagnostic; Predictive, Prescriptive, Autonomous), [19] (L1 Descriptive; L2 Informative; L3 Predictive; L4 Living), [20] (Cognitive), and [11] (Intelligent). The connections and similarities between these

definitions are given in the taxonomy through the categories “broader”, “narrower”, “related” and “closeMatch”.

Wind energy practitioners can use these definitions in different ways. For example, they can use the definitions to describe a given digital twin application, or they can use them to plan future developments. In Section 3, we describe how digital twins with different *system functionalities* can be applied to a range of wind energy use cases. This exercise can be repeated by practitioners for other dimensions. It should also be pointed out that the DITTA is continuously being updated. This process is being coordinated in the WeDoWind Information Modelling Community [21], which aims to bring together all the existing and previous information modelling activities in wind energy in order to align and prioritise them. For this reason, the following is recommended to wind energy practitioners:

BPR5: Contribute actively to the further development of the DITTA, which can be done in the WeDoWind Information Modelling Community.

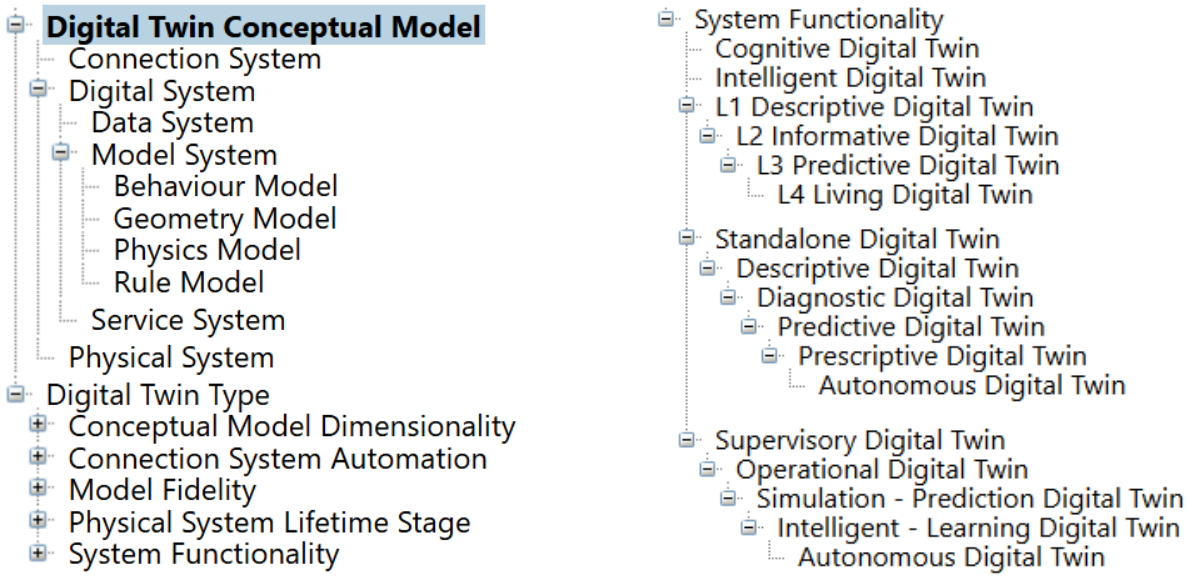

Figure 3. Overview of the DITTA [14]. Left: overall structure; Right: sub-classes inside the dimension “system functionality”.

4. Digital Twin Use Cases

This section presents a list of high-potential digital twin use cases for wind energy for different roles of actors in the sector, based on Step 5 from Section 1. This was also done iteratively in the group, by first making a suggestion using the results of the literature review, and adding and refining as required. The full table can be accessed at [22], and an excerpt is shown in Table 1 below. The first column divides the use cases by role (Project Developer, Project Owner/Operator Independent Service Provider, OEM / Component Manufacturer, Policy Maker / Regulator), the second column describes a specific activity that could be carried out using a digital twin, and columns 3-7 describes the use case resulting from each type of *system functionality*, as defined in the DITTA [14]. The definitions were used from [17] as described in Section 3 above. From left to right, the complexity and the capabilities of the resulting digital twin implementation increase. This table is not intended to be exhaustive, but instead illustrative. Readers are encouraged to treat it as a starting point: if a relevant use case is found to be missing, it can be entered in our List of Additional Use Cases found in the DITTA WeDoWind space [21]. Therefore, the following is recommended to wind energy practitioners:

BPR6: Contribute to our centralised and evolving list of high-impact digital twin use cases. Missing or newly emerged use cases should be contributed to the List of Additional Use Cases in the DITTA WeDoWind space.

Table 1. Excerpt from the list of digital twin activities and use cases for five different functional capabilities from [21].

Role	**Activity**	**Digital twin use case**				
		Supervisory	**Operational**	**Simulation/Prediction**	**Intelligent/Learning**	**Autonomous/Management**
Project Developer	Site selection	Ingest and store wind/wave simulation or onsite measurement data. Collect and display historical wind resource data or seabed baseline planning data. Collect and store climatic data (e.g, seawater temperature). Collect and display natural hazards historical data (e.g., earthquake catalogue)	Estimate energy production at different sites. Assess subsea and seabed condition	Simulate site-specific wind fields and uncertainty envelopes using regional–local coupled models to refine energy yield estimates.	Learn systematic biases in wind and seabed models from historical data and recommend improved site selection options.	Automatically optimise measurement system positioning (e.g. LiDAR or drone positioning) under predefined constraints.
	Environmental impact assessment	Monitor environmental measurements from on-site sensors.	Assess environmental measurements and define constraints.	Model interaction of turbine layout with local ecosystems, e.g. noise propagation simulations.	Learn environmental impact patterns, update ecological models and decide on compliant layout alternatives.	Automatically adapt environmental monitoring plans (e.g. sensor or drone deployment) in response to detected changes, subject to regulatory constraints.
Project Owner/Operator Independent Service Provider	Real-time turbine performance monitoring	Monitor SCADA, vibration, temperature, and electrical performance data.	Operate dashboards showing live performance KPIs.	Simulate wind turbine performance with an engineering model using wind measurement data as an input.	Use ML to detect abnormal patterns, refine performance models and make operational decisions.	Automatically trigger alerts and corrective actions for performance enhancement.
	Predictive maintenance	Track maintenance records and component status and deterioration indicators (e.g., corrosion).	Execute condition-based maintenance workflows.	Simulate the system in its current (deteriorated) state and predict faults to forecast component failures.	Continuously learn component degradation patterns using physics-informed prognostic models to refine RUL predictions.	Automatically propose and schedule maintenance actions within operator-defined planning and safety constraints.

OEM / component manufacturer	Blade aerodynamics optimisation	Collect design parameters and measurement data. Collect historical deterioration patterns/data.	Assess measurement data and compare to design parameters.	Run baseline simulations for new blade shapes and compare to measurements.	Learn performance patterns to optimise blade geometry.	Automatically generate optimised blade shape suggestions.
	Virtual validation of structural integrity testing	Review structural requirements and certification criteria, and ingest structural test data.	Assess structural test data.	Simulate stress and load distribution for new components.	Continuously learn structural performance/integrity metrics using data and physics-informed models to refine RUL predictions.	Automatically flag design weaknesses and propose improvements.
Investors	Financial performance optimisation	Track project financial indicators.	Operate financial dashboards with key KPIs.	Simulate financial performance under multiple scenarios to assess investment risk.	Learn relationships between operational performance, market signals, and policy drivers to refine risk and ROI models.	Automatically generate ranked investment and divestment scenarios to support portfolio decision-making.
	Portfolio monitoring and optimisation	Monitor all assets across the investment portfolio.	Benchmark project performance in real time.	Continuously monitor multiple wind assets in a portfolio to track financial KPIs and benchmark underperformance across projects.	Learn underperformance patterns and portfolio ESG risk correlations.	Run autonomous portfolio rebalancing recommendation engines.
Policy Makers / Regulators	National and regional resource assessment	Collect national wind and environmental data.	Operate mapping platforms and data portals.	Develop and maintain a wind atlas to guide site permitting, planning, and national energy strategies.	Learn regional patterns to improve resource prediction accuracy. Establish climate shift-related mitigation risk and adaptations.	Automatically update resource maps and policy recommendations.
	Policy and regulatory stress-testing	Review regulatory frameworks and constraints.	Operate compliance and policy evaluation tools.	Simulate the impact of new regulations on energy production, grid stability, and investment.	Learn policy impact patterns on production and grid stability.	Automatically generate regulatory scenarios and policy optimisation guidance.

5. Digital Twin Value Matrix

This section aims to help practitioners and decision-makers weigh up the expected added value and costs of introducing digital twin technologies to their specific applications. It was carried out in Step 6 of this work as introduced in Section 1. This was done during about six months by meeting once a month to discuss different real decision processes being carried out by members of the team and then by working together through one concrete use case.

In this section, a template matrix is introduced to assess the potential complexity and value of different digital twin functional capabilities for a particular activity. After that, an example application is introduced.

In this work, “potential value” is understood to mean the potential relative benefit that a digital twin functional capability can provide to stakeholders through technical, operational, economic, environmental, or societal improvements, independent of organisation-specific financial assumptions. Value reflects both intrinsic improvements enabled directly by the functionality, such as enhanced prediction accuracy or automation, and contextual impacts arising from downstream outcomes, including improved decision-making, reduced risk, or sustainability performance [23].

On the other hand, “potential complexity” is the potential relative level of technical, organisational, and infrastructural effort required to implement and operate a given digital twin capability, including the degree of system integration, data dependency, modelling sophistication, and coordination across assets, services, and stakeholders. This interpretation follows systems engineering perspectives in which system complexity increases with coupling, autonomy, data dependency, and decision automation [24]. In this study, complexity is therefore evaluated as implementation complexity, rather than algorithmic or computational complexity alone.

Together, these definitions allow the system functionality value matrix to support structured decision-making by comparing expected benefits against implementation effort before detailed economic modelling is undertaken.

5.1 Template matrix

Table 2 shows a template matrix for assessing the potential complexity and value of different digital twin functional capabilities of wind energy digital twins for a particular activity (column 2 from Table 1), inspired by [17]. For a given activity (column 2 of Table 1), it allows the potential relative complexity and its potential relative value for the five dimensions of a digital twin model according to [15] to be compared by evaluating the minimum requirements of the physical system, the connection system and the digital system. The complexity is given by the number and type of infrastructure or technology stacks required to achieve the required functional capabilities. The value is given by the intrinsic value and the contextual value. Both complexity and value use a colour scale from yellow to purple, where yellow means “least favourable” and purple “most favourable”. Therefore, “most favourable” corresponds to high value and low complexity.

Reading the rows from left to right, additional value and complexity are indicated with a “+”. The complexity or value potential changes colour only when additional minimum requirements of the physical system, the connection system and the digital system are introduced, i.e. when a new “+” is entered into the cell. A blank cell means that changing the functional capability does not lead to a change in the complexity or value, respectively. This colour scheme allows the potential value and complexity to be assessed visually as well as quantitatively, as described below. The entries in the matrix are meant as indicators, which should be expanded on for a given application, as discussed in Section 5.2 below.

For the potential complexity , the **physical system** increases in complexity from “Supervisory” (passive asset and sensor monitoring), to “Operational” (including sensor uncertainty and calibration handling), to “Simulation/Prediction” (access to turbine controllers and controllable actuators), to “Intelligent/Learning” (integration of adaptive and responsive components), and finally to “Autonomous/Management” (fully autonomous systems such as self-operating drones and automated asset management). The **connection system** increases in complexity from “Supervisory” (simple one-way sensor data streams), to “Operational” (data feeding into simulation models via manual or automated one-way coupling), to “Simulation/Prediction” (simulation results feeding back into model configuration), to “Intelligent/Learning” (near real-time, two-way coupled systems), to “Autonomous/Management” (edge computing with direct controller integration enabling automated system response). The **digital system model** increases in complexity from “Supervisory” (asset and component identifiers), to Operational (geometric and geospatial models), to “Simulation/Prediction” (physics-based and surrogate models), to “Intelligent/Learning” (data-driven and Bayesian models), to “Autonomous/Management” (behavioural and rule-based models enabling self-directed decision-making). The **digital system data** increases complexity from “Supervisory” (sensor data storage and multi-source integration), to “Operational” (storage of analysis results), to “Simulation/Prediction” (structured and defined metadata), to “Intelligent/Learning” (standardised semantics supporting interoperability), to “Autonomous/Management” (context-rich, machine-interpretable data enabling automated reasoning and control). The **digital system services** increases in complexity from “Supervisory” (dashboards), to “Operational” (data analysis tools and code), to “Simulation/Prediction” (physics-based, data-driven, or hybrid solvers including uncertainty quantification (UQ), verifications and validation (V&V), and visualisation), to “Intelligent/Learning” (decision support systems and model updating), and finally to “Autonomous/Management” (automated control algorithms and grid-level optimisation).

For the potential value, the main categories are “Reduced OPEX”, “Reduced CAPEX”, “Increased revenue”, “Improved community impact”, “Improved environmental impact”, “Improved energy security”, “Improved supply chain”, and “Workforce benefits”, with the increase

in value given from left to right in the table. The benefits are expected to vary depending on the activity, stakeholder type and external conditions, such as national policy, economic situation, or global catastrophes.

For practical application, Table 1 provides high-impact digital twin use cases across roles. Decision-makers could first choose the relevant activity from Table 1, and then use Table 2 to map a given use case to its functionality level. For this, it is recommended to define the required other dimensions, such as the connection system automation, model fidelity, and lifecycle stage. If a decision has to be made regarding these other dimensions, it is recommended to repeat the analysis with these dimensions as columns in Table 1, instead of the functional capability. Table 2 should be populated with specific activity-relevant details, and then used to evaluate potential complexity vs. value. The task of inserting case-relevant details into Table 2 may involve changing the general text regarding the "complexity" section to specific tools, adding new or more specific examples of value to the "value" section, and changing the colours, if appropriate. Therefore, the following is recommended to wind energy decision-makers:

BPR7: Weigh up potential complexity and value of different functional capabilities for a new digital twin development for a given activity by applying the "System functionality value matrix template" from Table 2 and populating it with problem-specific details.

An example of how this could be done is described in Section 4.2.

5.2 Example application

In Table 3 below, an example of an application of the "System functionality value matrix template" for a real decision is shown. In this decision, an OEM carrying out optimisation of blade aerodynamics is in the process of deciding whether to invest in enhancing their digital twin capabilities. In order to make this decision, the OEM did the following:

(1) Selection of activity from Table 1

The OEM first looked in Table 1 and selected the relevant activity, "Blade aerodynamics optimisation". For this activity, the five suggested digital twin use cases for the five functionalities from Table 1 are:

- **Supervisory:** Collect design parameters and measurement data. Collect historical deterioration patterns/data.
- **Operational:** Assess measurement data and compare to design parameters.
- **Simulation/Prediction**: Run baseline simulations for new blade shapes and compare to measurements.
- **Intelligent/Learning:** Learn performance patterns to optimise blade geometry.
- **Autonomous/Management**: Automatically generate optimised blade shape suggestions.

At the moment, this particular OEM has a digital twin at the "Simulation/Prediction" stage, and is considering investing to move it to the next capability of "Intelligent/Learning". The other dimensions introduced in Section 2 are not included in this decision and remain consistent as follows:

- **Connection system automation:** Partly “One-way coupled” (there are some automated processes for comparing measurements to simulations, but no automated model updating)
- **Model fidelity:** According to the definition in the DITTA, the digital twin has a “medium fidelity”, because the models used capture the dominant structure and behaviours needed for the target decisions, using a moderate number of parameters and moderate resolution.
- **Lifecycle stage:** Digital Twin Prototype (at the moment, the OEM is at the prototype stage)

(2) Population of Table 2 with specific details

In order to populate Table 2 with specific details of this activity, the OEM then made a copy of Table 2 and made the following changes and additions, which are shown in Table 3:

For the **potential relative complexity**, the **physical system** increases in complexity from "Supervisory" (wind turbine prototype, met mast, lidar, SCADA system, load sensors, cameras and surface pressure sensors [25]), to "Operational" (with no additional complexity), to "Simulation/Prediction" (with additional uncertainty and calibration information for sensor data), to "Intelligent/Learning" (with no added complexity), to “Autonomous/Management” (with additional components needed to access the wind turbine controller for real-time testing of geometry improvements, for controllable actuators for hypothesis testing and for autonomous drones making wind measurements). The **connection system** increases in complexity from "Supervisory" (data stream from met mast, SCADA system and other sensors), to "Operational" (no additional complexity), to "Simulation/Prediction" (with wind data additionally being automatically fed into the OEM’s HAWC2, Flex5 or OpenFAST models to define input conditions), to "Intelligent/Learning" (where additional components are needed to compare simulated loads and pressure distributions with measurements and to update the simulation set-up automatically), and ultimately to "Autonomous/Management" (where the loads and pressure data is used in near real-time data stream to optimise blade shape with actuators and to optimise the controller). The **digital system model** increases in complexity from "Supervisory" (with SCADA system labels) to "Operational" (with additional wind turbine geometrical models and location geospatial models) to "Simulation/Prediction" (using Flex5, HAWC2 or OpenFAST models) to "Intelligent/Learning" (with additional data-driven inflow inference models from the pressure distribution measurements [26]), and "Autonomous/Management" (with additional behaviour models and rule-based models). The **digital system data** increases in complexity from "Supervisory" (on-site data acquisition of sensor data, transferred to local servers) to "Operational" (storage of analysis results on local server) to "Simulation/Prediction" (with Flex5, HAWC2 or OpenFAST output format, and the time series are compliant with IEC 61400-13 [26] and stored in FAMOS, Flex5, HAWC2 or OpenFAST format) to "Intelligent/Learning" (with no increased complexity because standard semantics are not required at this prototype phase), and finally to "Autonomous/Management" (again with no increase in complexity). The **digital system services** increases in complexity from "Supervisory" (in-house dashboard for data visualisation) to "Operational" (with an additional in-house tool for data analysis, including calculation of Damage Equivalent Loads) to "Simulation/Prediction" (with an additional in-house tool for comparing simulations and measurements and UQ according to IEC 61400-13 [26]) to "Intelligent/Learning" (with an

additional Python code or in-house tool extension for decision support and model updating), and finally to "Autonomous/Management" (with additional control algorithms and grid control functionalities).

For the **potential relative value**, the two main categories were defined as “Increased profits through improved design (designer role)” and “Reduced OPEX through time saving (operator role)”. For “**Increased profits through improved design (designer role)**”, the “Supervisory” type does not provide any value. The “Operational” type provides improved understanding of wind turbine behaviour. Additionally, the “Simulation/Prediction” type provides improved load prediction accuracy, improved correction factors for future designs, and improved confidence in the simulations for new turbine designs. The “Intelligent/Learning” type adds improved design through configuration decisions, e.g. vortex generators or static yaw set-up, to this, and the type “Autonomous/Management” could result in more robust designs through wind turbine control, active pitching, or the introduction of active flaps. For “**Reduced OPEX through time saving (operator role)**”, the “Supervisory” type does not provide any value. The “Operational” type provides improved performance of existing turbines by altering static controller settings or retro-fitting performance enhancing devices, and improved advice on the use of lidar for improving operations. The “Simulation/Prediction” type adds improved efficiency and effectiveness of performance-enhancing recommendations through simulation of non-measured cases, and improved fault detection. The “Intelligent/Learning” type adds improved site-specific operating decisions, e.g. how to change polars to account for dirt on blades, and extends the analysis for many wind turbines and compares expected increase in performance to real turbines, as well as improved maintenance decisions. The “Autonomous/Management” type adds improved site-specific wind farm control in real time, e.g. yaw and pitch conditions.

(3) Comparison of options

The OEM then used the resulting Table 3 to compare the potential relative value and complexity of moving from a “Simulation/Prediction” digital twin to an “Intelligent/Learning” digital twin. It can be seen that moving from a “Simulation/Prediction” digital twin to an “Intelligent/Learning” requires the following four increases in potential complexity:

- The **physical system** does not increase in complexity from “Uncertainty and calibration information for sensor data”.
- The **connection system** increases in complexity from “Wind data automatically fed into HAWC2, Flex5 or OpenFAST models to define input conditions” to “Simulated loads compared with measured loads, simulation set-up updated automatically”.
- The **digital system model** increases in complexity from “Flex5 or OpenFAST or HAWC2 model” to “Data-driven inflow inference models from the pressure distribution measurements”.
- The **digital system data** does not increase in complexity from “+Flex5, HAWC2 or OpenFAST output format; Time series compliant with IEC 61400-13 and stored in FAMOS, Flex5, HAWC2 or OpenFAST format.”.
- The **digital system services** increase in complexity from “In-house tool for comparing simulations and measurements and UQ according to IEC 61400-13” to “Python code or in-house tool extension for decision support and model updating”.

The average relative complexity score moves from 2.6 to 3.2, assuming that yellow scores one and purple scores five, linearly increasing between these colours.

Moving from a “Simulation/Prediction” digital twin to an “Intelligent/Learning” results in the following increases in potential value:

- For the **designer role** (increased profits through improved design), the potential relative value increases from “Improved loads prediction accuracy”, “Improved correction factors for future designs”, “Improved confidence in the simulations for new turbine designs” to “Improved design through configuration decisions, e.g. vortex generators or static yaw set-up”.
- For the **operator role** (reduced OPEX through time saving), the potential relative value increases from “Improved efficiency and effectiveness of performance-enhancing recommendations through simulation of non-measured cases” and “Improved fault detection” to “Improved site-specific operating decisions, e.g. how to change polars to account for dirt on blades”, “Extend the analysis for many wind turbines and compare expected increase in performance to real turbines”, and “Improved maintenance decisions”.

The average potential relative value score moves from 2.0 to 3.0, assuming that yellow scores one and purple scores five, linearly increasing between these colours.

This comparison can now be used by the OEM to improve performance of existing wind turbines and future designs by minimising the uncertainties in environmental conditions, readjusting operational parameters and aeroelastic models. The next step is for the OEM to monetise the expected improvements in value and complexity, with these results as a guide. For example, the OEM could translate complexity into task hour costs and infrastructure costs. For the operator role, they could monetise the increase in value based on the existing underproduction numbers of operating turbines, and the expected improvements, e.g. an x% increase in production per turbine multiplied by the number of turbines in the fleet. For the designer role, they could monetise the increased efficiency brought about through more accurate simulations.

Table 2. System functionality value matrix template (with representative examples of increasing complexity and increasing value).

	Supervisory	**Operational**	**Simulation/Prediction**	**Intelligent/Learning**	**Autonomous/Management**
Potential relative complexity (more favourable = purple → yellow)					
Physical system	The asset and sensors, wind measurement devices		+Sensor measurement uncertainty and calibration information		+Access to wind turbine controller +Controllable actuators +Autonomous drones
Connection system	Data stream from sensors		+Data fed into simulation models	+Results fed back into simulation set-up	+Near real-time data stream, two-way coupling, on-edge compute, controller connection
Digital system model	Assets/component identifiers	+Geometrical models, geospatial models	+Physics models, surrogate models	+Data-driven models, Bayesian models	+Behaviour models +Rule-based models
Digital system data	Sensor data storage, integration of multiple sources	+Storage of analysis results	+Defined metadata	+Standard semantics	
Digital system services	Dashboards	+Data analysis code/tools	+Physics-based, data-driven, or hybrid solvers, UQ, V&V, simulation visualisation	+DSS, model updating +Dashboards, alarms, anomaly detection	+Control algorithms, grid control
Potential relative value (more favourable = purple → yellow)					
Reduced OPEX	Improved operating diagnostics	+Less down-time	+Improved prediction accuracy	+Improved operating decisions	+Improved wind farm automation
Reduced CAPEX	Improved design diagnostics	+Improved wind turbine design	+Improved wind farm layout	+Improved design decisions	+Improved wind farm control
Increased revenue	Improved turbine availability	+Improved turbine performance		+Reduced risks	
Improved community impact	Transparent monitoring of community-relevant indicators (e.g. noise, visibility).	+Assessment of monitored indicators against agreed thresholds	+Simulation of visual, acoustic, and environmental impact scenarios	+Learning from impact data & stakeholder feedback to recommend mitigation options	+Automated generation and evaluation of mitigation options under constraints
Improved environmental impact	Improved environmental indicators	+Assessment against regulatory or ecological limits	+Simulation of environmental impacts and mitigation scenarios	+Improved policies based on learned environmental response patterns	+Improved wind farm control
Improved energy security	System-level visibility of availability status		+Simulation of stress and disruption scenarios	+Improved resilience planning. reduce risks	
Improved supply chain	Improved tracking of components	+Improved supply chain planning		+Learning supplier and logistics patterns to improve planning	+Automated optimisation of logistics and scheduling
Workforce benefits	Improved situational awareness for operators and engineers	+Improved use of staff skills	+Use of simulated scenarios for training and safety analysis	+Optimal deployment of crews based on intelligent DSS	+Improved scheduling, safer operations

Table 3. System functionality value matrix template: example of application for the activity "Blade aerodynamics optimisation".

	Supervisory	Operational	Simulation/Prediction	Intelligent/Learning	Autonomous/Management
Potential relative complexity (more favourable = purple → yellow)					
Physical system	Wind turbine prototype, met mast, lidar, SCADA system, load sensors, cameras, pressure distribution sensors		+Uncertainty and calibration information for sensor data		+Access to wind turbine controller for real-time testing of geometry improvements +Controllable actuators for hypothesis testing +Autonomous drones making wind measurements
Connection system	Data stream from met mast, SCADA system and other sensors		+Wind data automatically fed into HAWC2, Flex5 or OpenFAST models to define input conditions	+Simulated loads and pressure distributions compared with measured loads and pressure distributions, simulation set-up updated automatically	+Loads data used in near real-time data stream to optimise blade shape with actuators and to optimise the controller
Digital system model	SCADA system labels	+Wind turbine geometrical models and location geospatial models	+Flex5, HAWC2 or OpenFAST model	+Data-driven inflow inference models from the pressure distribution measurements	+Behaviour models +Rule-based models
Digital system data	On-site data acquisition of sensor data, transferred to local servers.	+Storage of analysis results on local server	+Flex5, HAWC2 or OpenFAST output format +Time series compliant with IEC 61400-13 and stored in FAMOS, Flex5, HAWC2 or OpenFAST format.		
Digital system services	In-house dashboard for data visualisation	+In-house tool for data analysis, including calculation of Damage Equivalent Loads	+In-house tool for comparing simulations and measurements and UQ according to IEC 61400-13	+Python code or in-house tool extension for decision support and model updating	+Control algorithms, grid control
Potential relative value (more favourable = purple → yellow)					
Increased profits through improved design (designer role)		Improved understanding of wind turbine behaviour	+Improved loads prediction accuracy +Improved correction factors for future designs +Improved confidence in the simulations for new turbine designs	+Improved design through configuration decisions, e.g. vortex generators or static yaw set-up	+More robust designs though wind turbine control, active pitching, or the introduction of active flaps
Reduced OPEX through time saving (operator role)		Improved performance of existing turbines by altering static controller settings or retro-fitting performance enhancing devices, Improved advice on the use of lidar for improving operations	+Improved efficiency and effectiveness of performance-enhancing recommendations through simulation of non-measured cases + Improved fault detection	+Improved site-specific operating decisions, e.g. how to change polars to account for dirt on blades + Extend the analysis for many wind turbines and compare expected increase in performance to real turbines +Improved maintenance decisions	+Improved site-specific wind farm control in real time, e.g. yaw and pitch conditions

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