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Redefining Digital Twins – A Wind Energy Operations and Maintenance Perspective

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Redefining Digital Twins – A Wind Energy Operations and Maintenance Perspective

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Abstract. Digital Twin (DT) technology has seen an explosion in popularity, with wind energy no exception. This is particularly true for Operations & Maintenance (O&M) applications. However, this expanded use has been accompanied by loose, conflicting, definitions that threaten to reduce the term to a buzzword and prevent the technology from meeting its full potential. A number of attempts have been made to better define and classify DTs, however, these either oversimplify the term or tighten criteria, leading to the exclusion of many DT applications. A new definition framework dubbed the Digital Twin Family Tree is therefore proposed. This widens "Digital Twin" to a general umbrella term for the technology, accompanied by specific definitions. DT Tags are also used to provide individualised characteristics for implementations. A sector-specific definition was devised for component and system monitoring and predictions in wind energy O&M dubbed a CS-DT and suitable DT Tags created. The proposed framework was used to review existing research in literature, demonstrating the potential for increased understanding, explainability, and accessibility of DTs for expert and non-expert stakeholders.

1. Introduction

1.1. Defining Digital Twins

Digital Twin (DT) technology has seen an explosion in popularity [1], with wind energy no exception. Numerous implementations have been proposed, particularly for Operations and Maintenance (O&M) [2]. [3] provide one of the most commonly referred to DT definitions [4] through the lens of NASA and U.S. Air Force vehicles, stating that '*A Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin'*.

Attempts have been made since to improve DT definitions. [5] highlight an increasing trend towards the inclusion of DT functionalities and use-case-specific features within definitions from 2011 onwards. As an example of this, [1] categorised 30 DT definitions. Overall, the following definition of a DT was synthesised: '*A set of **adaptive models** that emulate the **behaviour** of a physical system in a **virtual system** getting **real time data** to update itself along its **life cycle**. The DT replicates the physical system to predict failures and opportunities for changing, to prescribe <u>real time actions</u> **for optimizing and/or mitigating** unexpected events observing and evaluating the operating profile system'*. However, this conflicts with the variety of DTs that exist. For example, supervisory DTs do not require predictive capabilities, highlighting the issue with trying to define a wide-ranging technology.

Despite this increasing complexity, a notable trend in DT research is a lack of understanding surrounding the term. [6] highlight that there is still little consensus on what the term means or what constitutes a DT. This might suggest a more generalised definition could be useful.

[7] postulate that '*a digital twin is defined as a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making'*. A definition echoed by [6].

However, generalised definitions risk reducing the term to a point where much of the meaning is lost. [8] describe DTs as an executable virtual model of a physical asset or system, drawing criticism for rebranding existing concepts [9]. This highlights the care needed in deciding defining features that ensure differentiation from other technologies. One solution may be that "Digital Twin" is better suited as a generalised umbrella term but with sector-specific DT implementations defined separately.

1.2. Classifying Digital Twins

Frameworks have also been proposed to categorise differing approaches to DTs, which often vary with level of sophistication and application. One approach is categorisation based on core capabilities. The University of Sheffield's Advanced Manufacturing Research Centre outlines 3 DT types based on abilities [10]; supervisory, which displays the live state of a real asset or process, interactive, which can take control of an asset to allow further monitoring or improve performance, and predictive, utilising provided data to generate predictions of a future assets state for more-informed decision making.

DTs have also been categorised by maturity level. [11] present 3 levels. Partial, where minimal asset data sources are used, providing a DT capable of measuring key metrics and identifying correlation between data sources. Clone, all meaningful data sources are used, providing a DT capable of undertaking prototyping. Augmented, measured data sources from an asset are combined with other datasets, such as historical data taken from analytics and algorithms.

DTs can also be categorised by their hierarchical position. [12] identified 3 unique positions. Unit level, a DT of an individual system. System level, using data from several unit level DTs to provide an overview of a wider system. System of a system (SoS) level uses data from multiple system level DTs to enable collaboration between different departments or institutions with differing goals.

Other frameworks look to separate DT-based technologies on how closely they resemble an idealised DT. One prominent approach is the differentiation between Digital Model (DM), Digital Shadow (DS), and DT as described by [13]. The terms are distinguished from each other based on having either a manual or automatic method of data exchange between a model and a twinned asset. A DM comprises 2 manual dataflows, therefore a change in either physical or virtual object has no direct effect on the other. A DS consists of an automatic dataflow from physical to virtual but manual in the reverse and therefore sees a change of state in a physical asset observed in the digital object but not vice versa. A DT is made of automated data flows in each direction and therefore a change of state in a real asset is observed in the digital version and vice versa.

Classification frameworks can have contrasting characteristics. A predictive system DT that has a manual dataflow from the virtual model to the asset may be considered a Predictive DT [10] or a DM [13] depending on the framework used. Furthermore, to fully appreciate a DTs implementation it may require the use of multiple frameworks. Highlighting that a DT is supervisory, capable of prototyping, and forms part of a wider system level DT would require the use of 3 separate frameworks [10, 11, 12].

Certain frameworks are also up to interpretation as to how they are applied, leaving room for misunderstanding and misuse. In defining DM/DS/DT how the term "automatic" is interpreted could lead to differing understandings of what constitutes both a DS and a DT, ranging from the digital object taking control of the physical object [13] to the triggering of manual reactions, such as the undertaking of maintenance activities [4]. [14] found that over half of research which claimed to utilise DTs was based on DM or DS concepts. This suggests either a high level of misconception as to what constitutes a DT or a range of interpretations for which the DM/DS/DT framework is unsuitable.

In light of this, there have been proposals for classification frameworks that amalgamate and consider many different characteristics. [6] provide a particularly relevant example, presenting a 0-5 capability scale for DTs in wind energy to consolidate DT definitions. 0 represents a standalone description of an asset that may not yet exist. 1 provides a live description of asset state. 2 expands on 1, providing additional diagnostic information useful for condition monitoring. 3. Includes predictive capabilities thus giving prognostic capabilities. 4 provides prescriptive recommendations using risk analysis and uncertainty as a basis. 5. introduces autonomous abilities, thus replacing human operator decision-making. The scale proposed allows for clear intuitive levels based on whether a DT has reached that stage, with new capabilities unlocked as the scale progresses. Whilst this provides an accessible understanding of DT capabilities, this is not without drawbacks. The scale proposed requires generalisation and as such processes powering certain capabilities are not disclosed, making 2 DTs that have similar abilities but alternative methods appear the same.

1.3. Digital Twin Technologies and Applications For Wind Energy Operations and Maintenance

O&M activities enable the continuous operation of a wind farm [4], with offshore O&M particularly challenging. Distance from the shore and hazardous weather conditions limit vessel access [15, 16]. This can result in costly delays and reduced generation [15]. DTs are one way of improving maintenance abilities, particularly given the high costs incurred [4], reflected in the increasing interest in O&M DTs.

[2] outline 4 key areas of DT applications within offshore wind O&M; failure monitoring and remaining life prediction, safety and ecological management, O&M decision-making, and design optimisation. DT technology for failure monitoring and remaining life applications has seen particular interest, with much more limited research within the remaining 3. [17] proposed a physics-based DT for structural reliability monitoring of offshore wind substructures. [18] outlined a framework for predicting support structure failure utilising a mixture of data-driven and physics-based modelling. [19] designed a data-driven DT for predicting mooring line failure for floating offshore wind turbines. DTs have also been proposed for more generalised system monitoring, including power generation prediction [20, 21].

1.4. Digital Twin Stakeholder Considerations

It is considered that there are 2 primary groups when discussing DT definitions and classification; expert and non-expert stakeholders. For experts, the use of numerous definitions and classification schemes may be achievable but time-consuming. Furthermore, navigating the vast sea of publications, even from a sector-specific perspective [2], is challenging. Non-expert stakeholders may lack an understanding of what defines a DT, separates it from similar technologies, and the underlying methods used [6] making their involvement more difficult.

Stakeholder involvement from experts and non-experts is likely to be required for DTs to reach their full potential, similar to many adjacent technologies. For example, explainability has become an increasingly hot topic in Machine Learning (ML), with stakeholder engagement helping to ensure robustness, comprehensibility, and future improvement [22].

Frameworks have been devised that look to consolidate and simplify DT definitions and classification [6], however do so in a way that masks implementation-specific details. Whilst this aids in simplifying DT concepts, this may make deeper involvement in DT design and creation more difficult. Furthermore, the lack of detail may be unsatisfactory to DT experts when assessing implementations.

1.5. Research Justification and Contributions

DT classification either requires multiple frameworks or all-encompassing definitions that risk masking differences in how different sectors, applications, and individual implementations can lead to very different DTs. It is considered that this may impede both expert and non-expert involvement in DT discussion and design. Given the unique challenges in O&M for wind energy, including the potential involvement of various stakeholders, it is considered that a definition and classification scheme better reflecting this area is needed. This paper's main contributions can be summarised as follows:

The creation of a novel definition for DTs in wind energy O&M. Given the interest, this has been tailored to component and system monitoring and prediction in wind energy and achieved by considering DT as an umbrella term, allowing for a more well-defined, sector-specific definition dubbed a CS-DT.

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The use of a Family Tree framework combining the above CS-DT definition with DT Tags, highlighting features unique to individual DT implementation. In doing so, DT classification schemes are combined. This is distinguished from existing methods by spanning from a top-level understanding to details concerning individual deployments, providing information useful to experts and non-experts.

The framework aims to bolster the understanding of CS-DT implementations for experts and non-experts, providing an aid in assessing the vast CS-DT literature that exists and increasing stakeholder involvement in implementations. Additionally, the framework aims to make the applicability and viability of CS-DTs easier to discern.

2. Redefining Digital Twins

2.1. Digital Twin Family Tree Overview

This research looks to provide an all-encompassing umbrella term for DT technology, allowing for a sector-specific DT definition for component and system monitoring and prediction in wind energy. To complement this, DT Tags add implementation-specific detail (see Figure 1).

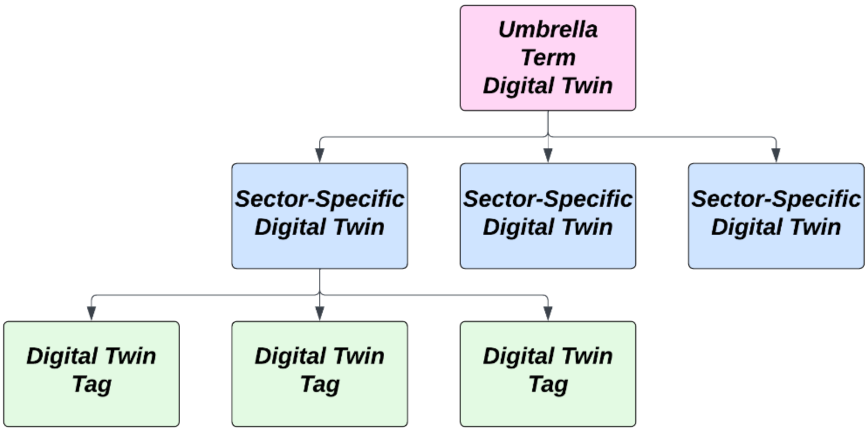

Figure 1. Digital Twin Family Tree Framework

2.2. An Umbrella Term Digital Twin Definition

An umbrella definition, based on existing definitions, reviews, and implementations has been proposed and looks to be inclusive whilst maintaining the technologies' uniqueness. Notable omissions compared to other definitions include a lack of a direct link between an entity and its virtual representation, allowing the use of exclusively external data instead, and not necessitating live or automatic updates, so to be exclusive of manual data sources. This results in the following DT definition:

*A **physical or virtual entity** linked to a **virtual representation** which updates so to be reflective of entity changes resulting in a **useful output**.*

2.3. Sector-Specific Digital Twin – Component and System Monitoring and Predictions

The broader umbrella DT term allows for a sector-specific definition, devised for component and system monitoring and predictions, dubbed a CS-DT. A number of elements were considered for the CS-DT based on existing implementations. These include the use of automatically received data, such as Supervisory Control and Data Acquisition (SCADA) [18, 20], that allows for timely updates. This may be supplemented by manual updates, including service logs and manual testing, useful for failure detection [18]. Given the focus on wind farm-related components and systems, an emphasis is put on any twinned assets being physical commercial components, with a variety of virtual model types and complexities involved. Applications are commonly intended for direct action either to the twinned asset or its associated wider system [18, 19, 20] ranging from human-only [20] to full automation [16] actions. The above considerations result in the following CS-DT definition (illustrated in Figure 2):

*A **virtual representation** of a commercial **components(s) or system(s)** required for wind farm operation generated through the use of a **data link** providing live updates on component changes that result in **direct action** to the twinned asset or the wider system it belongs to.*

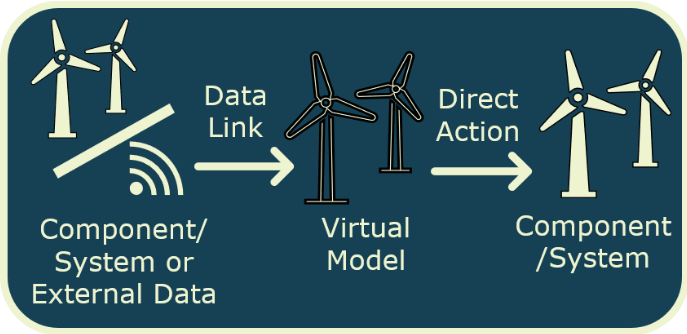

Figure 2. CS-DT Elements

2.4. Digital Twin Tags

These provide further identifying characteristics that make a DT unique in its implementation, giving key information and consolidating existing classification frameworks. These are informed by existing classification schemes and implementations considered to be CS-DTs [17, 18, 19, 20, 21, 23, 24]

2.4.1. Operational Updates. Describes how a CS-DT can receive data from a twinned entity. Considered to be via 2 main methods; **Automatic** (data is received without human input) and **Mixed** (data is received both automatically and via human input).

2.4.2. Intelligence Level. Indicates the intelligent capabilities of a CS-DT. This has been simplified to **Monitoring** (raw data displayed), **Predictive** (provides predictions of future asset state), and **Prescriptive** (provides courses of action based on predictions).

2.4.3. Intelligence Source. Identifies the source of intelligence level. Sources considered include **Data-Driven** (ML models), **Physics-Based** (physics models), or **Hybrid** (combining ML and physics).

2.4.4. Validation Metric. The method of validation and associated scores (where applicable) for the primary goal of the CS-DT. For example, the validation of intelligence source models, such as Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

2.4.5. Action Type. How actions resulting from a CS-DT are undertaken. Considered to be **Automatic** (no human input), **Manual** (human input) or **Mixed** (both automatic and manual actions undertaken).

2.4.6. Hierarchy Position. Consideration of the wider system a CS-DT may belong to [12]. Can be considered at **Unit Level** (individual DT), **System Level** (wider overview using multiple Unit Level DTs) and **System of a System (SoS) Level** (collaboration enabled using multiple System Level DT).

2.4.7. Deployment Stage. Stage of CS-DT development and deployment. Those considered are **Theoretical Framework** (exists as a framework only), **Deployed Test-Data** (implemented but using a test dataset and structure), and **Deployed Real-World** (implemented using data and structure as they would be for a real-world deployment).

2.4.8. Link Type. Designates the source of incoming data. Those considered include **Direct** (data received from the twinned asset), **External** (data from a separate source), or **Mixed** (using both sources).

Wind Energy Operations and Maintenance Framework Implementation

2.5. Case Study Application 1

The proposed Digital Twin Family Tree framework has been applied to 2 case studies to demonstrate its potential for aiding the understanding of academic literature and increasing stakeholder engagement.

In case study 1 a DT is developed to predict wind speed and power generation [21]. Live wind speed forecasts (provided by an external source) are upscaled to give forecasted wind turbine hub-height wind speeds utilising a k-Nearest Neighbour (kNN) regression model. A second kNN model then predicts power generation using these hub-height wind speeds. The DT is tested using historical data and a live full deployment is demonstrated. The application of the proposed framework is shown in Figure 3.

The CS-DT definition raises that this implementation is aimed at wind energy O&M for components and/or systems and characterises it as having a direct, tangible, impact on the twinned asset. Furthermore, the DT Tags provide a concise understanding of how this specific CS-DT operates. For example, identifying that external data sources are used, with ML providing intelligent capabilities. This may make the process of sorting through literature more effective. Furthermore, the framework enables greater general stakeholder involvement, by lowering the barrier to understanding the complexity of the system. For example, understanding that a data-driven model is used may raise ideas that physics or hybrid approaches could be tested instead. Additionally, knowledge of a real-world and validated deployment may increase confidence in the CS-DTs viability from an O&M industry perspective.

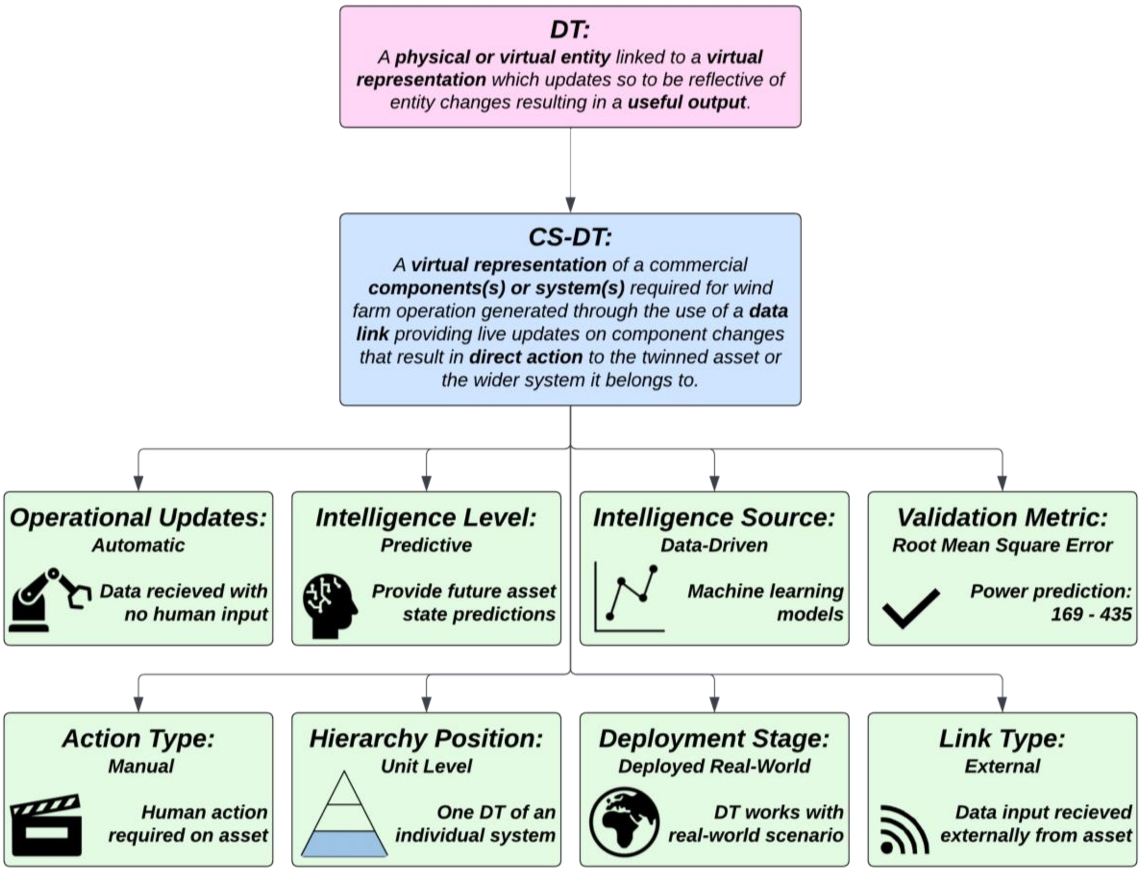

Figure 3. Case Study 1 Framework Implementation

2.6. Case Study Application 2

Case study 2 follows a proposed DT framework for monitoring offshore wind support structures [18]. The system utilises a mixture of sensor, non-destructive testing, and service data to model and predict potential degradation using data-driven and physics-based models. Bayesian networks predict structural fatigue cracking, aiding the development of a custom task plan tailored to the size of damage, with an intelligent decision module providing recommendations. Application of the definition framework is shown in Figure 4. Given that the DT and CS-DT definitions remain the same these have been omitted. Whilst both case studies cover the implementation of a CS-DT, the proposed definition framework highlights there are several differences. Case study 2 utilises a direct link, meaning data is received from the wind turbine itself, and uses a mixture of automatic and human inputs. Furthermore, both machine learning and physics are used for predictions, which is expanded further through prescriptive capabilities. Case study 2 is also shown to be only in an early development stage and not validated as a result. Knowledge of these differences may be of use when deciding which CS-DT is of use or in developing improvements for both academic and industrial O&M research and development.

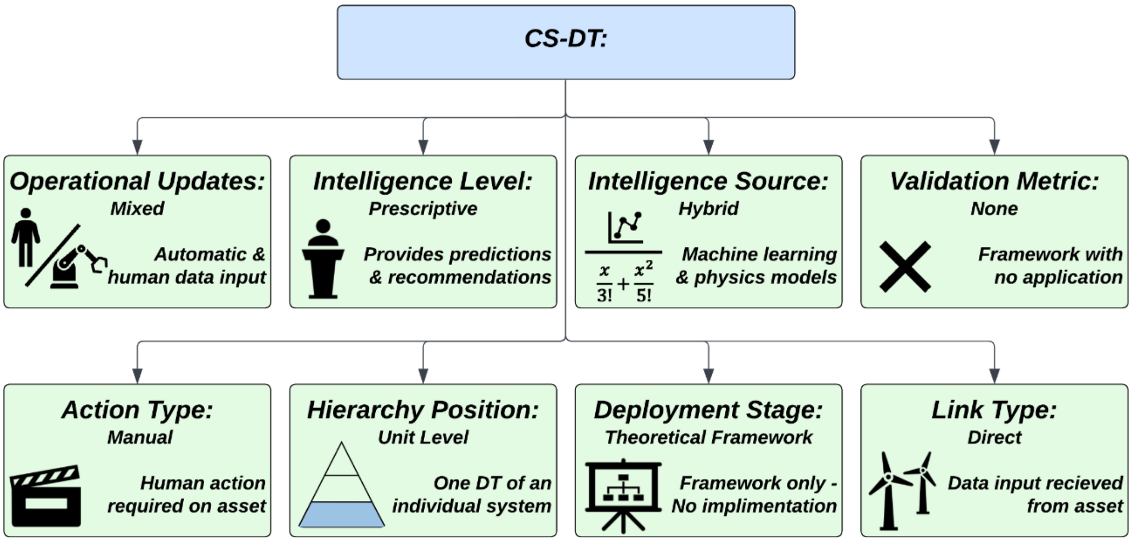

Figure 4. Case Study 2 Framework Implementation

2.7. *Comparative Assessment*

The Digital Twin Family Tree framework has been applied to select CS-DT implementations, covering wind energy O&M. Table 1 highlights a condensed list of CS-DT Tags generated through this. Select alternative classification schemes (as highlighted within the introduction section of this paper) have also been applied to these CS-DTs within Table 2.

Table 1. Application of Digital Twin Tags

Application	Operational Updates	Intelligence Level/Source	Validation Metric	Action Type	Hierarchy Position	Deploy Stage	Link Type
Support Structures [18]	Mixed	Prescriptive/ Hybrid	N/A	Manual	Unit	Framework	Mixed
Gearbox Drivetrain [23]	Automatic	Predictive/ Physics	N/A	Manual	Unit	Real-World	Direct
Support Structures [17]	Automatic	Predictive/ Physics	N/A	Manual	Unit	Test-Data	Direct
Mooring Lines [19]	Automatic	Predictive/ ML	MAE ≈15	Manual	Unit	Test-Data	Direct
Power Generation [21]	Automatic	Predictive/ ML	RMSE 169 - 435	Manual	Unit	Real-World	External
Power Generation [20]	Automatic	Predictive/ ML	MAE 264 – 295	Manual	Unit	Test-Data	Direct
Power Generation [24]	Automatic	Predictive/ Physics	MAPE 7.7%	Manual	Unit	Real-World	Direct

Table 2. Comparison of Existing Digital Twin Classification Frameworks

Application	[13]	[12]	[10]	[11]	[6]
Support Structures [18]	DS/DT	Unit	Monitoring/ Predictive	Augmented	Level 4
Gearbox Drivetrain [23]	DS/DT	Unit	Predictive	Clone	Level 3
Support Structures [17]	DS/DT	Unit	Predictive	Clone	Level 3
Mooring Lines [19]	DS/DT	Unit	Predictive	Clone	Level 3
Power Generation [21]	N/A	Unit	N/A	Partial	Level 3
Power Generation [20]	DS/DT	Unit	Predictive	Partial	Level 3
Power Generation [24]	DS/DT	Unit	Monitoring/ Predictive	Clone	Level 3

3. Discussion

DT discussion has suffered from a lack of understanding of what constitutes a DT [6]. Whilst other classification frameworks within wind energy have looked to identify unique characteristics or unify classification through generalisation, the proposed Digital Twin Family Definition framework provides a more comprehensive overview. The proposed framework was applied to 2 case studies, highlighting the potential usefulness by identifying individual features and differences between implementations.

For case study 1 the proposed framework highlights that this is a DT and more specifically a CS-DT (providing definitions for these) and identifies that this specific implementation receives automatic operational updates, and has predictive abilities powered by data-driven ML models which result in manual human action being undertaken on the asset. Furthermore, this is an individual unit level DT and has been tested using a real-world scenario that has been validated and uses data external to the asset. When comparing this to the alternative classification schemes [13] and [10] would not identify this as a DT, with [12] only identifying that this is a unit level DT. [11] would identify this as a partial DT due to its limited use of data. [6] would classify this as a Level 3 DT, providing monitoring capabilities, as well as predictive capabilities giving prognostic capabilities. It is considered that the inclusion of a specific definition for CS-DTs and the use of DT Tags helps to distinguish the sector-specific application of CS-DTs from more general approaches and provides a much more detailed understanding of individual implementations than the alternative classification schemes tested. Case study 2 showed how the framework makes discerning between different implementations easier, providing details that may be useful in deciding on which approach to use or ways to potentially improve upon proposed or existing CS-DT implementations when considering wind energy O&M.

Currently, the lack of understanding as to what constitutes a DT, both from experts and non-experts, risks stifling wind energy O&M DT development both in academia and industry [6]. It is therefore hoped that in defining and categorising CS-DTs whilst retaining knowledge of specific implementation that the proposed framework will empower both expert and non-expert stakeholders to have greater input in the design and improvement of wind energy O&M DT technologies and implementations. For experts, the proposed framework should make literature more easily accessible, allowing quicker and more effective understanding of individual CS-DT implementations and potential limitations. Non-expert stakeholders also benefit by having a greater understanding of what the DT implementation aims to achieve and how it does so through the DT and CS-DT definitions. Furthermore, DT Tags provide an understanding on an individual basis of how capabilities are achieved and the current state of development, lowering the barrier to involvement in CS-DT development. As highlighted within the case studies, the framework also provides details helpful to both academia and industry in determining the applicability and viability of a DT when considering wind energy O&M, including models used, current development stage, and validation of models.

However, it is acknowledged that increasing the level of detail may overwhelm a stakeholder, risking alienation rather than empowerment. It may be that the use of classification frameworks should be altered depending on the intended audience. For example, the use of the proposed framework may be more suited to groups likely to be involved in DT development, with broader audiences benefitting from a more simplified approach, such as that given by [6]. The usefulness of the DT Tags identified for individual implementation may also vary depending on the stakeholder.

Another major hurdle is in ensuring the adoption of the proposed framework. This is a challenge faced by the majority of classifications and definitions highlighted and it is perhaps telling that none of the existing DT classifications highlighted within this paper have been utilised within the academic DT implementations reviewed. The solution to this is likely larger than any one paper (or several) can provide and may be rooted in the same issues that have resulted in a lack of unity in terms of definitions, standards, and communication protocols [5].

Future work should look to validate the proposed definition framework and provide numerical quantification of its usefulness. This includes validation of the umbrella DT and sector-specific CS-DT definitions, the DT Tags proposed, and identification of alternative Tags. Furthermore, the framework should be tested against a wider sub-set of DTs including differing sectors related to wind energy.

4. Conclusion

Digital Twin (DT) technology has seen an explosion in popularity, bringing with it a range of, definitions, classification schemes, and a lack of clarity as to what makes the technology unique. This risks wind energy O&M DTs not meeting their potential. Definitions and classification schemes can often conflict and miss unique differences between sector-specific and individual DT implementations. This can make it hard for expert practitioners to navigate through the huge breadth of literature and exclude non-expert stakeholders, whose contributions ensure robust DT development and improvement.

This research has therefore proposed a Digital Twin Family Tree framework. This comprises a broad umbrella term for DT technology, allowing sector-specific DT definitions differentiated using new nomenclature. In addition, DT Tags add implementation-specific detail, differentiating individual applications and looks to unify existing classification frameworks.

The proposed framework was applied to component and system monitoring and predictions in wind energy Operations and Maintenance (O&M) via the creation of a CS-DT, and suitable DT Tags. Through the use of case studies, these were demonstrated to be able to better distinguish between CS-DT implementations than alternative classification frameworks. In part, due to the addition of implementation-specific information. It is hoped that in doing so CS-DT implementations are easier to understand, communicable, and inclusive to expert and non-expert stakeholders who are more empowered in CS-DT development. Furthermore, the proposed framework provides details helpful to both in determining the applicability and viability of a DT when considering wind energy O&M, including models used, current development stage, and validation of models.

Future work should look to validate the proposed definition framework with both experts and non- to provide numerical quantification of its usefulness. This could look to validate the umbrella DT and sector-specific CS-DT definitions proposed, the usefulness of the DT Tags, and identify alternative Tags that may be of use. In addition to this, the framework should be tested against a wider sub-set of DT applications including differing sectors related to wind energy.

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