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TNO report

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A Detailed Study of Digital Twins for Wind Energy Applications

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Summary

This report summaries the studies of wind energy digital twin applications in the project STRETCH (STate of art Rotor Extended To Create Higher performance), which is supported by Topsector Energiesubsidie from the Dutch Ministry of Economic Affairs under project TEHE118020. It also aims to inspire researchers in the field of wind energy digital twins, recognizing its modest contribution in the grand scheme of things.

This report begins by reviewing the background information on digital twins and proposes aligning the understanding of digital twins using the definition from the Digital Twin Consortium: a digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity. Following this definition, the report reviews digital twin applications from the literature and in the wind energy industry. For the academic research of wind energy digital twins, a simple digital twin structure consisting of three elements - data, model, and purpose - is introduced and elaborated upon. To architect a digital twin capable of representing the entire lifecycle of real-world entities and processes, a systematic methodology is needed. Model-Based Systems Engineering is a suitable approach for this purpose and is briefly discussed in this report.

Finally, two case studies are conducted and reported. Both case studies demonstrate promising applications of wind energy digital twins. The first case study involves using Ansys Twin Builder to create a reduced-order model (ROM) of a wind turbine blade FEM model. This ROM can run within seconds while maintaining high fidelity. It can be deployed for virtual sensors, virtual testing, what-if scenario studies, root-cause analysis, and failure model prediction, among other applications. The second case study focuses on building a digital twin framework for the rotor test rig developed within the STRETCH project to test wind turbine pitch bearings and hubs. The digital twin is used to gain a better understanding of the behaviour, loading, and dynamics of the tested assembly to optimize test preparations, expedite test setup, and reduce risks and delays during testing. The results from the digital twin model of the rotor test rig, including test articles, are encouraging, although further work is required to enhance accuracy and practicality.

Contents

1 Introduction

This report is written for the work package (WP) 3.1 on Digital Twin (DT) in the project STRETCH (STate of art Rotor Extended To Create Higher performance), which is supported by Topsector Energiesubsidie from the Dutch Ministry of Economic Affairs under project TEHE118020.

The aim of the STRETCH project is to contribute to the reduction of offshore wind Levelized Cost of Energy (LCoE) by being able to stretch the rotor diameter with minimal adjustments to the overall rotor, turbine, or substructure. This is achieved by innovations in rotor design, improvements in aerodynamical and structural modelling and innovation in testing methods as reported in the STRETCH project final report [1].

This report complies the results of the research works which have been done in STRETCH project about DT technology and serves as a detailed study of DT for wind energy applications.

In Chapter 2 the DT background, definition, literature research, industry applications and challenges and future are elaborated. Some reflection on the architecture of DT for wind energy application is given in Chapter 3. Chapter 3 also provides thoughts as wind energy researchers about how to understand DTs in the wind energy domain as summarised in Figure 52 and elaborated in Chapter 3. Moreover DTs should be capable of following the full lifecycle of a system, and MBSE (Model Based System Engineering) methodology matches well with DT engineering works by the DT definition and this is elaborated in Chapter 4. Chapter 5 to 6 are case studies of (Reduced Order Modelling) ROM and STRETCH rotor test rig DT framework respectively.

2 Wind Energy Digital Twin

As an emerging technology and buzz word for many years, how will DT technology change the wind energy sector is a natural question by any wind energy researchers. This chapter will try to answer this question from the origins of the DT concept, DT research, DT industry applications to the challenges and future of DT technology.

2.1 Background

DT is basically the name of a ***technology***, just like the names as IoT, blockchain or 5G. However this name is abused to represent DT products, DT systems, DT platforms, DT models, DT tools or DT solutions etc.

"Technology is the result of accumulated knowledge and application of skills, methods, and processes used in industrial production and scientific research."
- Wikipedia

The idea of digital twin technology was described in 1991 with the publication of Mirror Worlds by David Gelernter [2]. However Michael Grieves was credited with the first application of the digital twin concept in manufacturing and he publicly introduced the concept and model of the digital twin in 2002 for PLM (Product Lifecycle Management) at a conference in Michigan. Eventually John Vickers of NASA introduced the name 'Digital twin' in 2010 with the concept consisting of a physical product, a digital/virtual product and the connections between the two products. The term 'connections' here means the data/information that flow between those two products and the connections are driven by use cases and it is called Digital Thread nowadays as shown in Figure 1 .

It is interesting to mention that the motivation of DTs at that time was to move the work activities from the physical space in the 20th century to the virtual space in the 21st century aiming at substituting information from virtual space for 'wasted' physical resources such as all the mistakes made, failed try-outs [3].

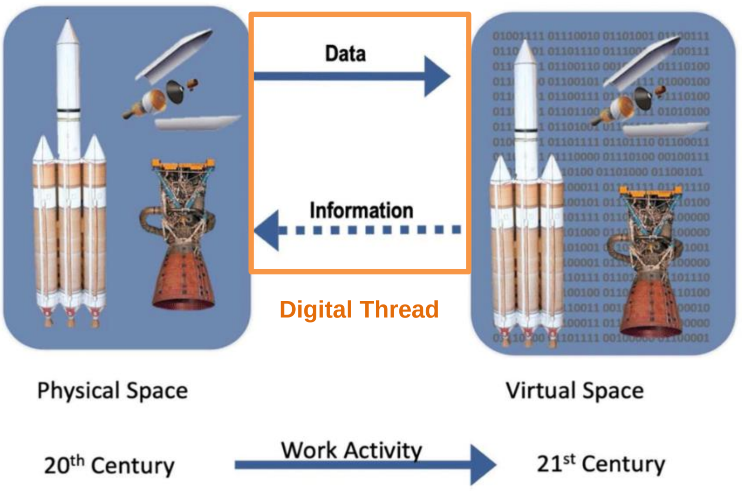


Figure 1 DT Model concept explained, Dr. Michael Grieves [4]

Hype Cycles from Gartner [5] characterize the progression of innovation in typically 3 stages: overenthusiasm, disillusionment and the eventual understanding of the innovation's relevance and role in a market or domain. In 2017 DT was listed by Gartner [6] as emerging technologies as one of the digital platforms together with 5G, edge computing, blockchain and IoT platform. It was considered as the next step in the IoT driven world where companies are increasingly leveraging IoT technologies in their digital business journey [7]. It continued on the list in 2018 as one of the digitalized ecosystems together with blockchain, blockchain for data security, IoT platform and knowledge graphs.

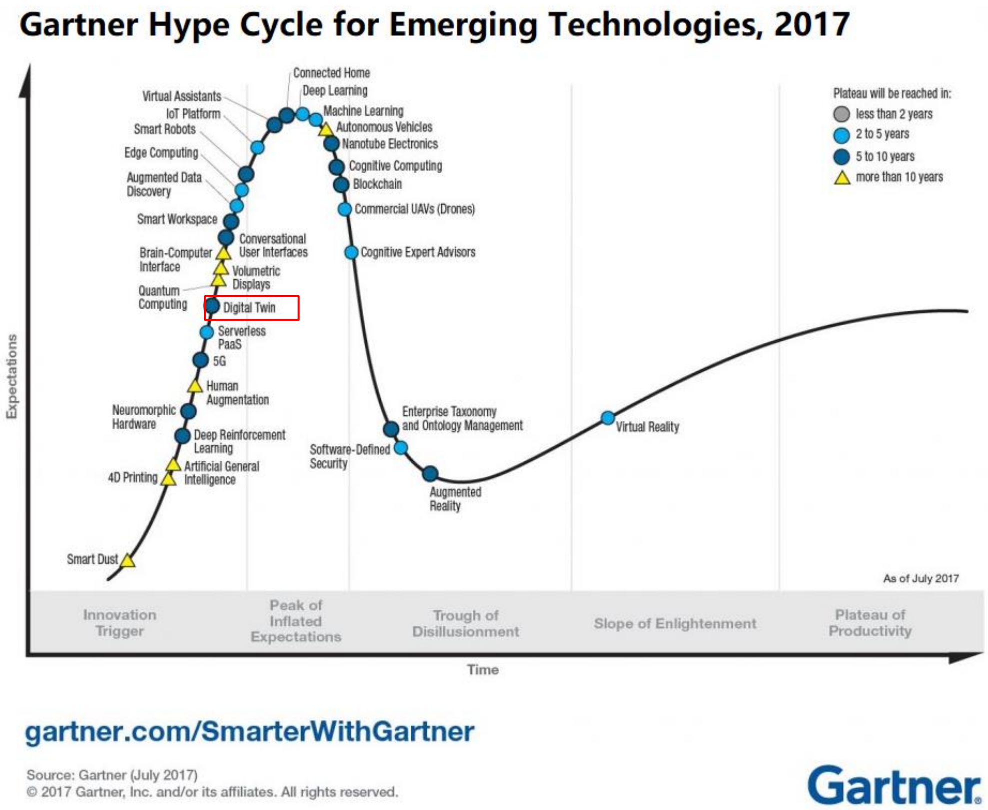


Figure 2 Garner Hype Cycle for Emerging Technologies 2017

"Digital twins add value to traditional analytical approaches by improving situational awareness, and enabling better responses to changing conditions, particularly for asset optimization and preventive maintenance." – Gartner 2017 [7]

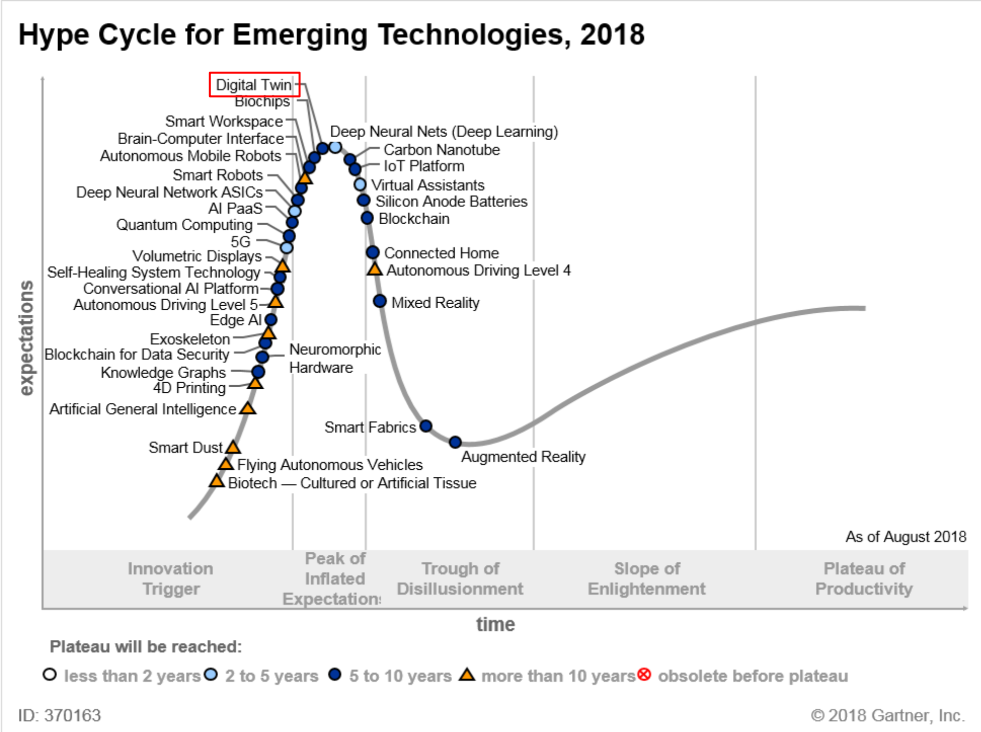


Figure 3 Garner Hype Cycle for Emerging Technologies 2018

“ Digital twins have huge potential benefits, but creating and maintaining them can be both risky and difficult” – Gartner 2018 [8]

In 2019, DT is not considered as emerging technology by Gartner anymore and disappeared on the Gartner emerging technologies hype cycle list. This means that DT technology is getting well recognized and accepted and going into the industry application phase as it is considered as No.4 of the top 10 strategic technology trends for 2019 [9]:

“The idea of a digital twin is not new. It goes back to computer-aided design representations of things or online profiles of customers, but today’s digital twins are different in four ways:

1. *The robustness of the models, with a focus on how they support specific business outcomes*
2. *The link to the real world, potentially in real time for monitoring and control*
3. *The application of advanced big data analytics and AI to drive new business opportunities*
4. *The ability to interact with them and evaluate “what if” scenarios”*

DT technology provides unique capabilities, but a DT, in itself, is composed from a number of technical capabilities to provide an overall solution [10]. As illustrated in Figure 4, the Digital Twin Consortium (DTC) categorizes the capabilities into 6 groups: data services, integration, intelligence, user experience, management and trustworthiness.

Evolving in the era of ‘Industry 4.0’ (revolution of data or Cyber-Physical Systems – the convergence of the physical world and the virtual world [11]) and the ‘second machine age' [12] (from muscle power to mental power), DT technology will develop further and provide more capabilities..

Figure 4 DT Capabilities Periodic Table Framework [10]

To conclude, the DT enablers and drivers can be summarised in figure below.

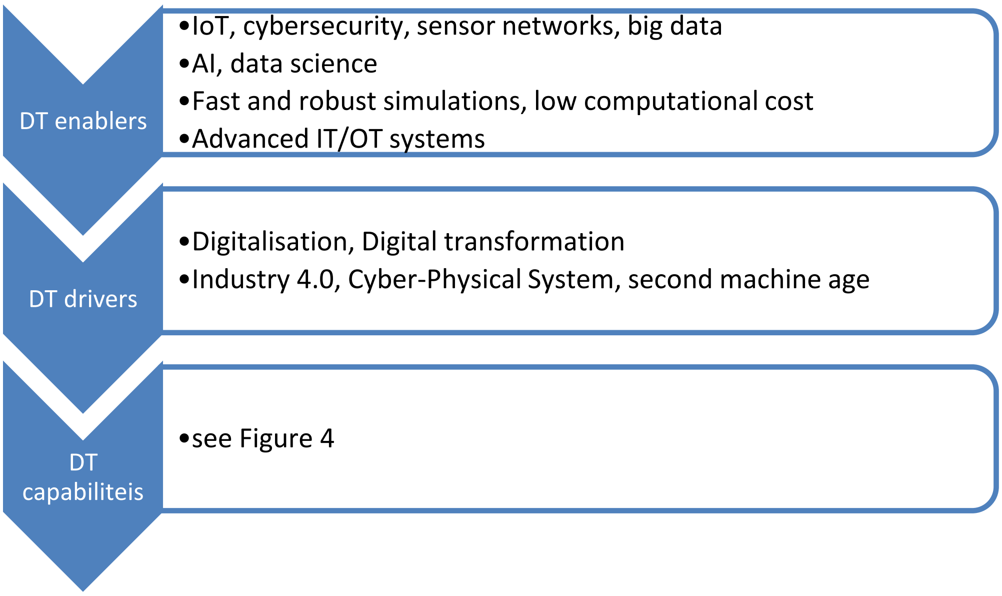


Figure 5 DT enablers and drivers

2.2 Digital Twin definition

All in all, what is a proper definition of DT? The author of this report would like to refer to the definition from the Digital Twin Consortium [13] to reach the consensus:

A digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity:

- *Digital twin systems transform business by accelerating holistic understanding, optimal decision-making, and effective action.*
- *Digital twins use real-time and historical data to represent the past and present and simulate predicted futures.*

- *Digital twins are motivated by outcomes, tailored to use cases, powered by integration, built on data, guided by domain knowledge, and implemented in IT/OT systems.*

2.3 State of the art of DT technology for wind energy application

Wind energy industry was born with rich data, e.g. wind data, simulation data, operation data , maintenance and inspection data etc. Therefore it embraces the DT technology quite naturally to enable the potential values of those big data.

In this chapter Scopus is used to find relevant literature about wind energy digital twins. After searching “wind AND digital twin” (in August 2022), 34 documents (17 conference papers, 15 articles and 2 reviews) are found. The number of those documents by year is shown in Figure 6. Note that only articles, conference papers and reviews are counted in Scopus search.

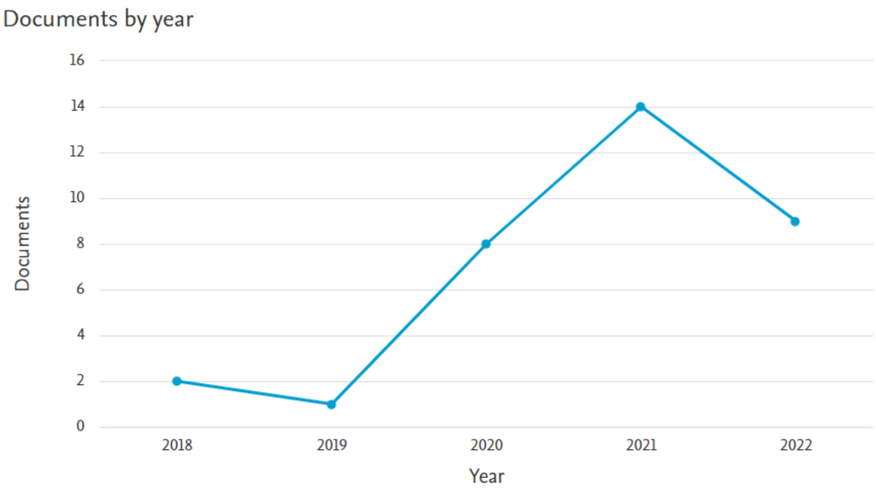


Figure 6 Wind energy digital twin documents by year from Scopus search August 2022

The earliest one [14] is from 2018 and it is also the mostly cited. In this article, a framework is established for a complete digital twin platform for optimum predictive maintenance strategy.

Based on titles and abstracts from the 34 documents, a word cloud is plotted in Figure 7 to have a general impression of the contents. The size of the a word is proportional to its appearance frequency.

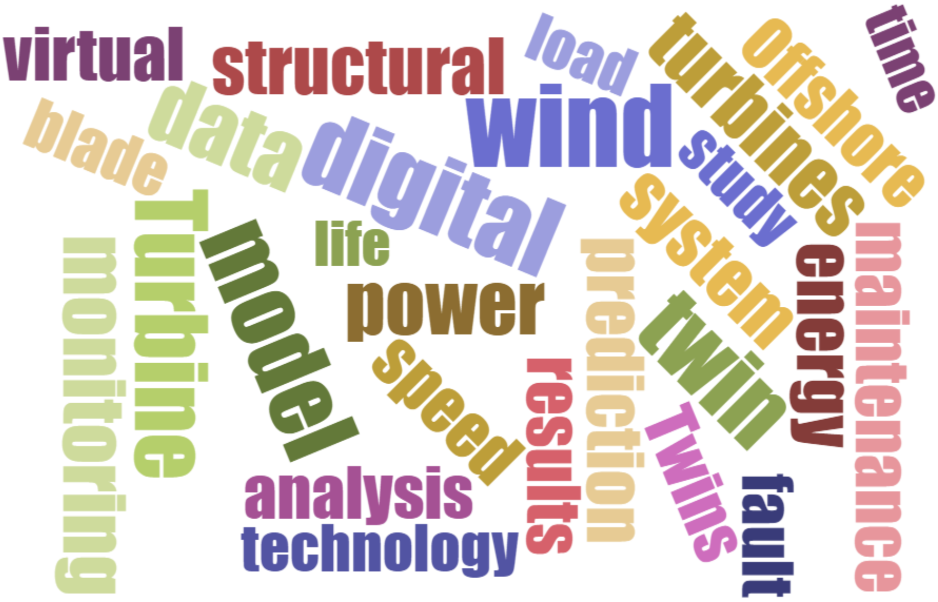


Figure 7 Most frequent words in the titles and abstracts of 34 documents found in Scopus

Based on those frequent words, one could see that building DTs (model, data, analysis, technology) for applications such as monitoring, maintenance, prediction, virtual sensing for offshore turbines and blade are the majorities.

To better categorize the papers, a thorough review of the papers is done to identify the research focus as summarized in table below.

Wind energy DT research focus	Relevant papers
Virtual sensing	[15] [16]
Maintenance	[17] [18] [19]
Monitoring	[20](load and lifetime) [21] [17] [22] [23] [24]
System solution	[25] [26] [18]
Fault	[16](detection) [18](prediction) [27] [21] [28] [29] [17](detection)
Prediction	[30](power) [22](mooring tension) [18](fault) [19](lifetime) [31] [32](ws)
Model and data	[33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] [44] [45]
Highlights in the table: Data-driven Physics-based Hybrid **No highlights: not applicable**	

Table 1 Literature categorized into different research focus

The reference number of the papers are highlighted accordingly to the method used. 'Data driven' refers to the DT model built up using statistics methods or AI methods. 'Physics based' refers to the DT model built up using physics theories and equations.

‘Hybrid’ means the combination of the two methods above. The irrelevant papers are not highlighted as the focus on the relevant topic but no model developed.

Virtual sensing is about using the results from the virtual part to sense the non-measured physical part, or a data driven model to replace or support physical sensors.

The modern maintenance can be categorized as reactive maintenance, preventive maintenance, condition-based maintenance, predictive maintenance and prescriptive maintenance [46]. Prescriptive maintenance is also known as the knowledge based maintenance of optimizing maintenance based on predictions and it is proactive and intelligent. Wind energy DTs are used for condition-based, predictive and prescriptive maintenances, and DTs are considered as mandatory part of prescriptive maintenance [17].

Most monitoring studies are on the more general operation conditions side, but there is also monitoring on specific targets such as load and lifetime.

System solution is about bringing many component level simulations to integrated system level to provide holistic understanding.

Fault related DT is about failure or fault detection or prediction.

Prediction related DT is about predicting states, operating paramerters etc. It can vary up to the objects to bepredicted.

Model and data related DT studies focus on high fidelity and fast or real-time data driven or physics based models and advanced data science algorithms.

It is also interesting to see the documents by year if only search for the key word: digital twin. As shown in Figure 8, the digital twin topic starts booming from the year 2017 (61 documents) and reach the peak in 2021 (1607 documents). This trend matches well with the DT as the listed Gartner emerging technologies in 2017 in Figure 2. Note that only articles, conference papers and reviews are counted in Scopus search and 1991 is set as it is the year of born of DT idea.

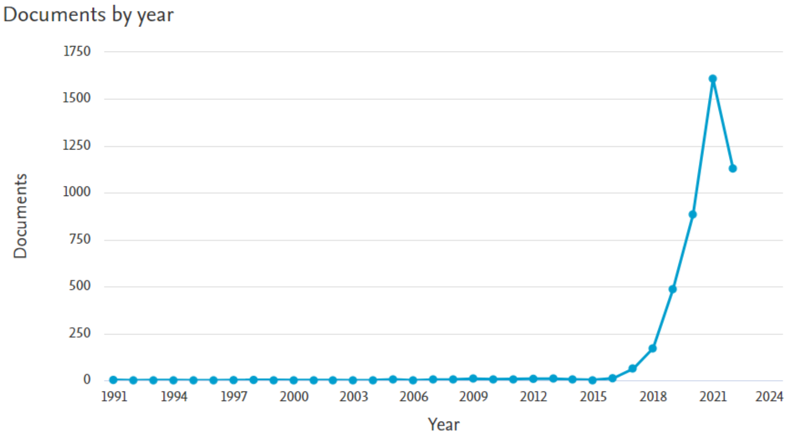


Figure 8 Digital twin documents by year from Scopus search August 2022

Based on the literature study, the following characteristics are concluded in this report to distinguish DT technology with other terms:

- It is incubated during the emergence of IoT technology
- It is one digital technology among digitalisation.
- It is a purpose driven technology of building a digital counterpart of a physical part with active connections between them. (i.e. it is motivated by outcomes, tailored to use cases, powered by integration, built on data, guided by domain knowledge, and implemented in IT/OT systems.)
- The physical part can be a component, asset, unit, system or process.
- The virtual part is model based. Data driven model or physics based model or both. Fast, sufficient fidelity for the dedicated purpose and low calculation cost.
- DTs should cover the lifecycle of the physical part and the active connections enable the virtual part to adapt to the dynamic changing environment to represent the (near or even) real-time status of the physical part. It can also trace back the historical status or predict future status.
- The physical part may not be modular designed but the virtual counterpart is modularly modelled.
- It evolutes with new technology alignment and new business objectives during the digitalization revolution.
- The inputs and outputs are traceable.

2.4 Industry application

DT has been widely embraced by industries [47] including the wind energy industry. There are many commercial DT platform providers. A list of the well-known DT platforms is presented below. Besides those from industry leaders, there are other DT platforms on the market. The different DT platform can be classified using the DT capabilities listed in Figure 4. All the commercial DT platforms are developed for those DT capabilities to certain extent.

- Microsoft - Model and interact with the real world, Azure Digital Twins
- GE - Predix Digital Twin
- IBM - Industry Transformation with IBM Digital Twin
- Siemens - Digitization in machine building
- Oracle - Digital Twins for IoT Applications
- DNV – Digital twin WindGEMINI for wind turbine operations

In the industry, DTs are well classified as component twin, asset twin, system twin and process twin. Most DT platforms are applicable for all those types and for different industries. Among those DT platforms listed above, DNV WindGEMINI is the only one dedicated to the wind industry.

It is worth highlighting that the intelligence capability of DTs can have three approaches: data driven approach, physics-based approach and hybrid approach. The data driven approach is still the main trend as it can directly analyze the collected data for immediate insights. The physics-based approach needs more deep domain knowledge. There are only few dedicated companies who can provide physics-based DT industry services such Ansys Twin Builder and Akselos RB-FEA. The hybrid approach is relatively new and only seen in a few references as shown in Table 1.

To better demonstrate the state of the art of wind energy DTs, several industry applications of successfully deploying DTs in the wind energy field are described below.

GE's DT [1]

GE Digital defines DT as a software representation of a physical asset, system or process designed to detect, prevent, predict and optimize through real time analytics to deliver business value. GE Wind is using GE DT technologies to market its Digital Wind Farm solution (Figure 9) which includes capabilities such as: Asset Performance Management (APM), Operation Optimization and Business Optimization - including Cloud Connect, Wind Fleet Excellence, Enterprise e-SCADA, and Wind Power Forecasting, for the entire fleet.

Based on available public information, it can be concluded that the intelligent capability of GE wind energy DTs are mainly following data-driven approach. Advanced AI or data science algorithms are integrated to provide data quality check, statistical pattern verification, trend detection/prognostics and component level analytics, and finally to increase revenue and reduce cost and risk.

Figure 9 Digital Wind Farm industry solution from GE Wind [48]

DNV WindGEMINI DT[2]

WindGEMINI can analyze data and provide actionable insights based on its 5 advanced algorithm modules:

- structural integrity monitor (uses frequency analysis algorithms to process higher frequency data from standard turbine interfaces to help detection of structural issues such as rotor imbalance and foundation degradation),
- power curve performance watchdog (using artificial intelligence algorithms to analyse SCADA data to identify power curve performance issues, incorrect turbine control settings, and sub-optimal operation),

[1] https://www.ge.com/digital/blog/what-digital-twin
[2] https://www.dnv.com/power-renewables/services/data-analytics/windgemini/

- pattern of production analysis (through monitoring the relative variation in production between turbines and over time to identify performance outliers and degradation in turbine performance)
- energy production analysis (analyzing SCADA data from the wind farm and mesoscale data to estimate the contribution of windiness, turbine availability and performance)
- turbine life estimator (leveraging DNV's physics based simulation models to calculate fatigue accumulation at the main structural components)

One of the interesting case studies[3] is that in 2019 the structural integrity monitor module highlighted a high level 1P activity at one of the turbines of a 40 MW wind farm in the USA. Then recommendation was made to inspect the pitch misalignment since it could result in high levels of imbalance. The inspections revealed a crack at the blade root, which is the likely cause of the increased 1P activity.

Ramboll DT[4]

Ramboll has been quite active in the wind energy DT business. Ramboll provides DT solutions as intelligent asset management for offshore structures such as platforms and wind turbines to reduce the costs of operation and maintenance and to provide decisions on whether to extend their lifetime. They introduced the 'true digital twin concept' which is a digital model continuously monitoring how the structure is doing and updated with real time information about the loads affecting the structure[5]. One of the application cases is what they did in the EU ROMEO project where an offshore wind turbine jacket support structure is modeled as shown in Figure 10 and Figure 11.

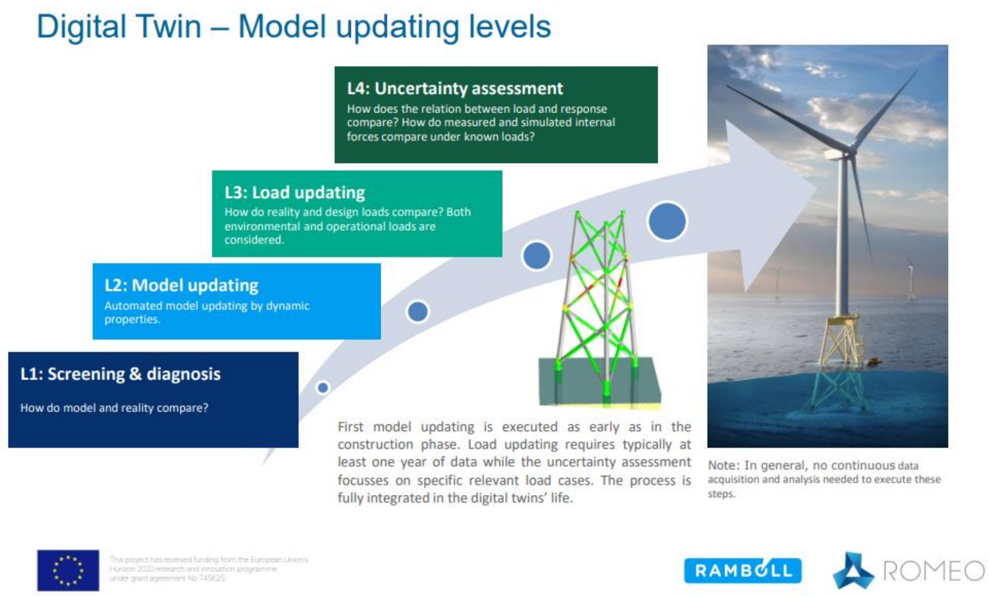


Figure 10 Ramboll DT application case from EU project ROMEO 2022 [6]

[3] https://www.dnv.com/power-renewables/services/data-analytics/windgemini/windgemini-cases.html?
[4] https://www.ramboll.com/operations-and-asset-management/digital-twin
[5] https://www.ramboll.com/insights/decarbonise-for-net-zero/true-digital-twins
[6] https://www.romeoproject.eu/wp-content/uploads/2022/04/Windeurope_2022_ROMEO_Ramboll.pdf

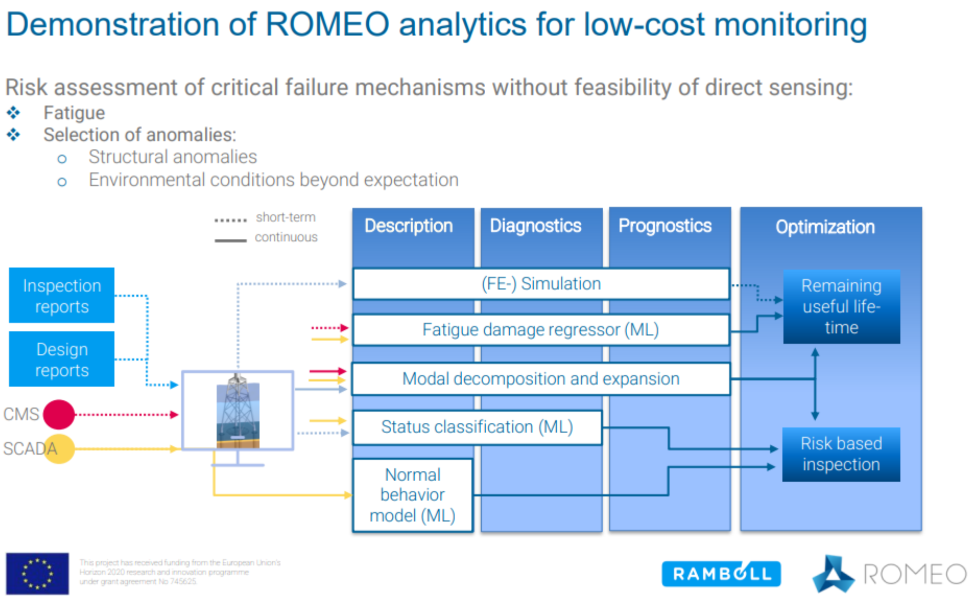


Figure 11 Ramboll DT application case from EU project ROMEO 2022 [6]

2.5 Challenges and future

As one technology, DT will evolve with the challenges coming from different aspects. From a modelling perspective, a list of challenges are summarized in Figure 12 in a paper [49]. Those challenges are considered more applicable for wind energy DT applications from a research point of view.

Challenges	Enabling Technologies
Data management, data privacy and security, data quality	Digital platforms, cryptography and blockchain technologies, big data technologies
Real-time communication of data and latency	Data compression, communication technologies like 5G and internet of things technologies
Physical realism and future projections	Sensor technologies, high fidelity physics-based simulators, data-driven models
Real time modeling	Hybrid analysis and modeling, reduced order modeling, multivariate data-driven models
Continuous model updates, modeling the unknown	Big data cybernetics, hybrid analysis and modeling, data assimilation, compressed sensing and symbolic regression
Transperancy and interpretability	Hybrid analysis and modeling, explainable artificial intelligence
Large scale computation	Computational infrastructure, edge, fog and cloud computing
Interaction with physical asset	Human machine interface, natural language processing, visualization augmented reality and virtual reality

Figure 12 Mapping between common challenges and enabling technologies [49]

Besides the challenges listed in Figure 12, the author of this report would like to highlight following challenges which are observed:

- Life cycle data collection
  Inside DT there is the digital thread which links the physical part and the virtual part as seen in Figure 1. To complete the digital thread, data sources from different stakeholdesr among the life cycle are needed. Such as the data from material supplier, component OEM, wind turbine OEM, wind farm

developer, logistics parties, installation parties and O&M parties etc. Unlike automotive industry, wind energy industry has quite silo data and many barriers for assessing the data from each stakeholder [50].

There is an approach called decentralized DT [51] to tackle this challenge. This approach proposes an aggregated model where all the training data is kept by each client so it enables sharing knowledge without sharing the actual data.

- Qualification and assurance of DT
  As explained by DNV [52], a physical product must go through rigorous assurance processes to meet regulatory requirements and company and/or industry standards. This also holds for a digital product i.e. DT.

  As a start and to create awareness, DNV has published recommended practices for data quality assessment, assurance of sensor systems, assurance of data-driven algorithms and models, assurance of simulation models. But since DT is constantly learning new skills and capabilities, it will be a long journey for DT qualification and assurance.

  Moreover, as DT technology is still in the exploring phase in wind energy industry, there is still a gap to bridge before it will be mature and standardized.

  Under this topic, a more specific research challenge is the model validation and uncertainty quantification (MVUQ) [53]: *DT models powerfully unite theoretical foundations, numerical models, and sensor data which include associated uncertainties and errors. The field of MVUQ research entails the development of methods and metrics to test model prediction accuracy and robustness while considering all relevant sources of uncertainties and errors through systematic comparisons against experimental observations*.

- Goal given to goal seeking
  Although wind energy industry is still exploring the goals of DT to create business values, the demanding of developing a DT which can seek the goal itself instead of giving a goal to DT is already there.

  Especially in the O&M field, the goal seeking capability is being asked to find the optimal solution by DT itself for multi-objective problems.

- Physics-informed data-driven models (or physics-AI model)
  There is a saying that garbage in and garbage out, and this is true for the ordinary data-driven model especially AI based or statistics based. There is a hybrid model which is data-driven and physics informed e.g. surrogate model, reduced-order model or reduced physics mode. This type of models still keep the high fidelity of physics-based models but are as fast as ordinary data-driven model.

- Move from asset-intensive applications to other fields: design, testing, process, system solution etc.

The current DT applications in wind energy industry are asset-intensive i.e. focusing on the applications for asset management. NASA introduced DT in 2010 for designing a rocket, not for asset management. There is little focus of using DT in design phase in wind energy industry yet.

3 Wind Energy Digital Twin Research

Chapter 2 provides a top-down view of wind energy DT. Just looking at the DT capabilities in Figure 4, it provides some thoughts for wind energy DT research. But it is too broaden and too scattered to focus – for a traditional wind energy research institute as TNO. Thinking from a different angle, the bottom- up view, what a wind energy research institute is rich of? The easy answer could be: domain knowledge and numerous data and models.

This chapter will discuss the wind energy digital twin research priorities based on following reasons:

- More focus on topics relevant to wind energy industry applications instead of the ordinary DT technology
- Break down the structure to sensible elements for wind energy domain expert

3.1 Breakdown DT elements

It is easy to picture a DT in mind consisting of 5 dimensions as shown Figure 13: physical entity (PE), virtual entity (VE), DT data (DD), services (Ss) and connection (CN) which is the connection among PE, VE, DD and Ss.

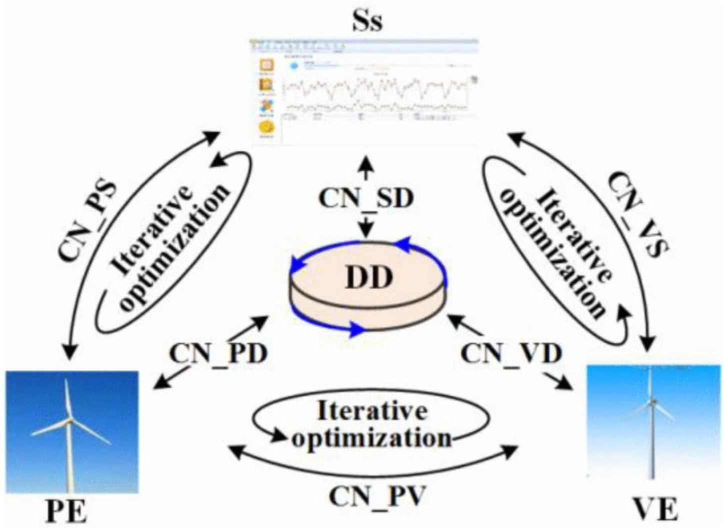


Figure 13 Five-dimension DT model for complex equipment [54]

Wind turbines are highly complex interacting mechanical and electrical systems, driven by turbulent (and largely unmeasured) environmental conditions. DT requires in depth domain knowledge to support its applications. Thinking about the wind energy DT with the specific domain knowledge, it can be simplified as in Figure 14 with just 3 elements: data, model and purpose.

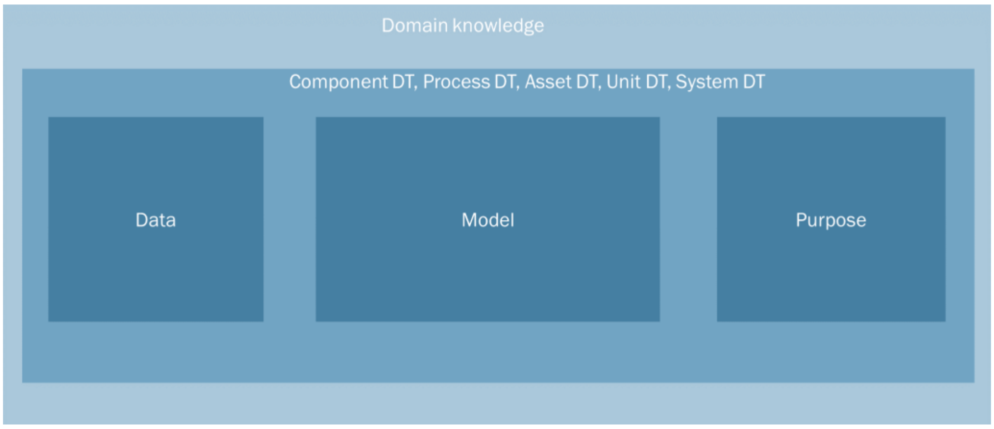


Figure 14 Wind energy DT elements governed by domain knowledge for different types of DT

3.1.1 Purpose

Any DT should start with a clear purpose: the industry needs should be understood and the specific DT technology capabilities should be targeted.

	Industry	Object	Challenges	
Solve	Oil&Gas	asset	cost	**Using DT technology**
	Aerospace	unit/system	efficiency	
	Automobile	process	reliability	
	Energy	component	quality	
	Wind Energy			

Figure 15 Understand industry needs - example

	DT technology capabilities				Business needs
Develop	Physical part	Virtual part	Connections	**for**	Cost reduction System integration Multi scenario Decision making Remote operation
	sensors	Data driven model	Monitoring		
	CMS	Physics based model	Data services		
		AI & ML algorithms	Integration		
		Hybrid models			

Figure 16 Targeted DT technology capabilities - example

For wind energy DT, the author of this report thinks the purpose can be concluded as 2 categories: cost reduction and system integration, as same as the objectives for digitalisation reported by ETIP WIND (European Technology & Innovation Platform on Wind Energy) [55] as shown in Figure 17.

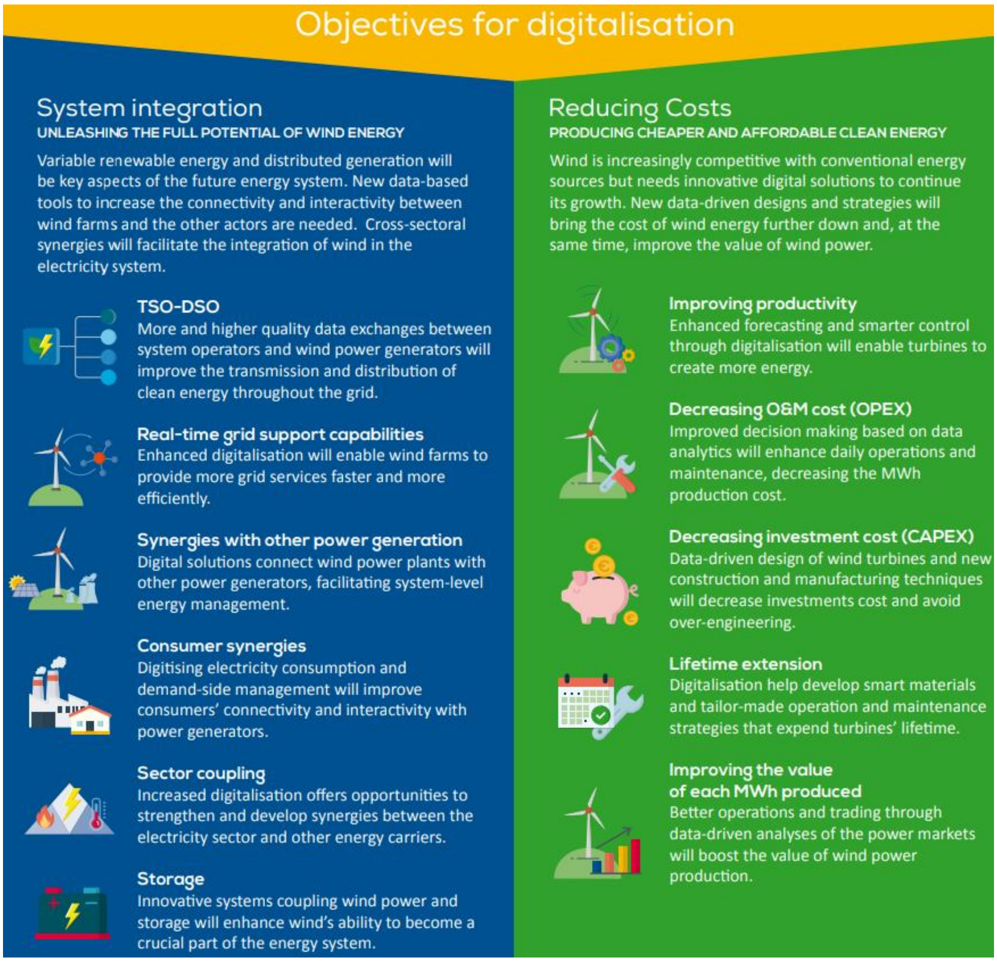


Figure 17 ETIP Wind report: an overview of the digitalisation potential for wind energy

3.1.2 Data

Wind energy was born with numerous data: simulation data from hundreds of design load cases (DLCs) required by Type Certification; prototype testing data; SCADA data used to monitor and control the turbine. Nowadays with the digitalisation evolution (ubiquitous digital connectivities), more and more databases are getting available too, such as environment data, production data, logistics and installation data, and advanced structural health monitoring data etc. To give an impression of the data, Figure 18 shows the complexity from a wind plant and Figure 19 purely shows the data from wind turbine asset management point of view.

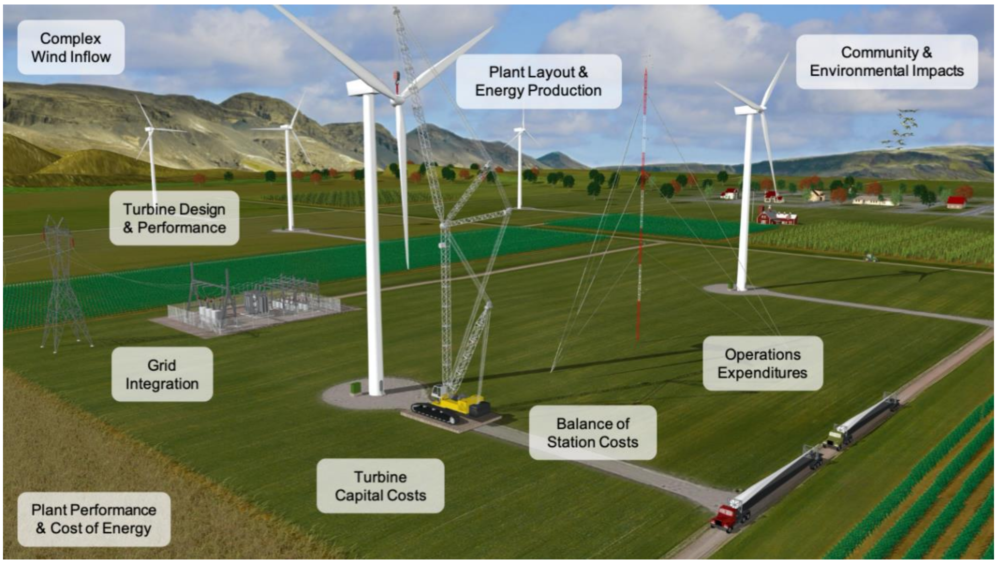
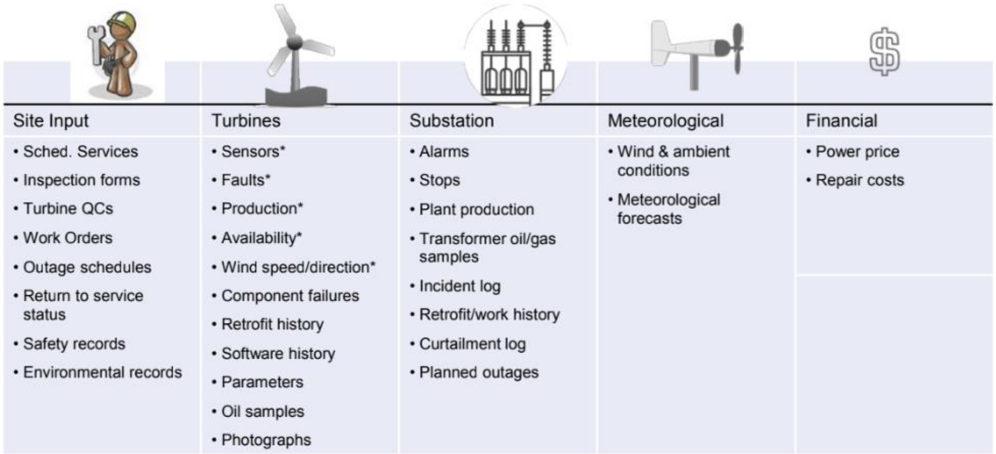


Figure 18 Wind Plant – a complex and highly interconnected system. Graphic by NREL for IEA Wind task 37: SE in Wind Energy[7]



Site Input	Turbines	Substation	Meteorological	Financial
• Sched. Services	• Sensors*	• Alarms	• Wind & ambient conditions	• Power price
• Inspection forms	• Faults*	• Stops	• Meteorological forecasts	• Repair costs
• Turbine QCs	• Production*	• Plant production		
• Work Orders	• Availability*	• Transformer oil/gas samples		
• Outage schedules	• Wind speed/direction*	• Incident log		
• Return to service status	• Component failures	• Retrofit/work history		
• Safety records	• Retrofit history	• Curtailment log		
• Environmental records	• Software history	• Planned outages		
	• Parameters			
	• Oil samples			
	• Photographs			

Figure 19 Basic wind turbine asset data (one PPT slide from IEA task 43[8]: wind energy digitalization)

As a summary, the wind energy data related challenges are presented in Figure 20 and briefly explained in following paragraphs.

Data

- Wind energy data sharing
- Wind energy data mining
- Wind energy data science tools/algorithms and best practices
- Wind energy data (real-time) modelling and management
- Wind energy data security and confidentiality
- Wind energy data quality criteria and assurance
- Wind energy data standardization
- Wind energy data ontology
- Wind energy advanced measurements/sensors

Figure 20 Wind energy DT - data challenges

- Wind energy data sharing

[7] https://iea-wind.org/task37/
[8] https://www.ieawindtask43.org/

Data is the cornerstone of DT, and the wind energy industry is awash with data. However the lack of data structuring and sharing has been a barrier from the beginning of wind energy digital revolution[9]. It is still not resolved but just getting more well recognized[10] and urgent[11] [12]. In general, the wind energy industry is beginning to move away from the “silo” mentality and unwillingness to share data[13]. However it is going slowly and limited to certain circumstances, e.g. turbine operational data only[14], wind resource data only or very old data.

- Wind energy data mining

As the state of the art, DT in wind energy industry is mainly used for asset management (i.e. product lifecycle management - PLM) applications to get insights of asset performance and take actions. Data mining is used there to reveal unknown, hidden and meaningful patterns from the data.

- Wind energy data science tools/algorithms and best practices

Together with the data mining and the development of data science, various data science tools and algorithms are deployed in wind energy industry.

- Wind energy data (real-time) modelling and management

Data collection is important, but to be able to use the collected data in real-time, a lot of data modelling (i.e. the process of analyzing and defining all the different data types the business collects and produces, as well as the relationships between those bits of data[15]) and management techniques are necessary to be demonstrated for wind energy use cases.

- Wind energy data security and confidentiality

How to obtain valuable information from the collected data, while maintaining the security and the confidentiality is still a research topic in wind energy industry.

- Wind energy data quality criteria and assurance

Garbage in and garbage out, this is a big concern of using data. New business models created by digital transformation already appears to tackle data quality assurance such as data certificates (data in compliance with DNV standards or best practices), or data value assessment (data suitable for a particular purpose, such as trend analysis or machine learning).

- Wind energy data standardization

Wind energy is well standardized with many existing ISO/IEC/DNV standards and wind energy data standards is not an exception. IEC 61400-25 series (i.e. communications for monitoring and control of wind power plants) are already released. IEC 61400-15 series are under development currently which aims for a framework for assessment and reporting of the wind resource, energy yield and site

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[9] https://www.nature.com/articles/529019a
[10] https://www.ieawindtask43.org/technical-area-2-data-standards
[11] https://www.powerengineeringint.com/digitalization/big-data/data-sharing-critical-to-wind-sectors-role-in-energy-transition/
[12] https://windeurope.org/newsroom/news/improving-data-exchange-between-wind-farms-and-the-power-system-is-central-to-a-cost-effective-energy-transition/
[13] https://www.wedowind.ch/wedowind-ecosystem
[14] https://www.o2owind.com/data-driven-collaboration
[15] https://powerbi.microsoft.com/

suitability input conditions for both onshore and offshore wind power plants. The development of IEC 61400-16 is going to start soon which aims for data format for power curves. It is expected that more wind energy data related standards will come in future.

- Wind energy data ontology

Ontology is 'a set of formally descripted concepts within a certain knowledge domain and the relationships between those concepts' [56]. As formal and explicit specifications of representing knowledge about a domain, ontologies are helpful in making information more shareable across people and computer models to support knowledge-based reasoning [56]. Speaking the same language is crucial when multiple stakeholders are involved. IEA Wind Task 37 has started the development of a suitable ontology for wind energy data[16] .

- Wind energy advanced measurements/sensors

Measure less properties will hinder the understanding of a wind turbine, but more measurements will increase the cost. The advanced measurements or sensors are trying to fill this gap. Moreover embedded sensors at the optimal locations of the structure will make the measurements more standardized and increase the value of measurements.

3.1.3 *Model*

Recall the DT definition at the end of Chapter 2.1: A digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity. Depending of the purpose of DT, the models as part of the DT should reach specified frequency and fidelity. For wind energy DT, the challenging areas for the model are listed in Figure 21 and explained in following paragraphs.

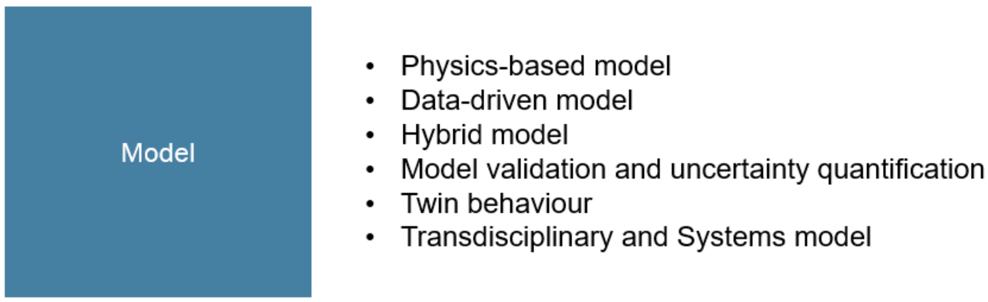

Figure 21 Wind energy DT - model challenging areas

- Physics-based model

Most numerical methods used in the industry are the result of deriving theoretical differential equations that are based on conservation laws, physical principles, or phenomenological behaviour from a particular process. These theoretical derivations and simplifications lead to many of the physics-based models which have been used nowadays.
With the increase of modern computation power, traditional high fidelity physics-based models can be solved much faster than before, but meantime the physics-

[16] https://windio.readthedocs.io/en/latest/

based models are also getting larger and more complex. It is a trade-off between accuracy and calculation time. For this reason, surrogate models can be created by 'simplifying' the traditional high fidelity physics-based models to reduce the simulation time and still preserving essential behaviour and accuracy. This also enables the potential of real-time solution.

ROM (reduced-order model) is based on model order reduction (MOR) techniques for reducing the computational complexity of mathematical models in numerical simulations. By a reduction of the model's associated state space dimension or degrees of freedom, an approximation to the original model is computed i.e. the ROM. ROM will be an important wind energy DT enabler for researchers to focus on.

In Table 1, physics-based model related references are listed for wind energy DT applications.

- Data-driven model

Except statistics methods and mathematic methods, AI (more specifically: ML) is also widely used for creating data-driven models. Wind energy industry players like OEMs, operators and service providers are quite active of using data-driven model because of large quantity of operational data they have. For data-driven model, the question is how accurate it can represent the physics.

In Table 1, data-driven model related references are listed for wind energy DT applications.

- Hybrid model

The physics-based model and data-driven model are both well known. The decision whether to use a data-driven or a physics-based approach depends on the conditions of the data availability, data quality as well as the knowledge level of the physical system itself.

The hybrid model referred in this report is the coupling, combination or interaction of a physics-based model and a data-driven model in order to take the advantages from both sides. The examples are: 1) use AI(ML) to train the results from a physics-based model to create a surrogate model; 2) augment a data-driven model with physics simulation for better model performance; 3) augment a physics-based model with measurement data behaviour model for reducing model uncertainty and error; etc.

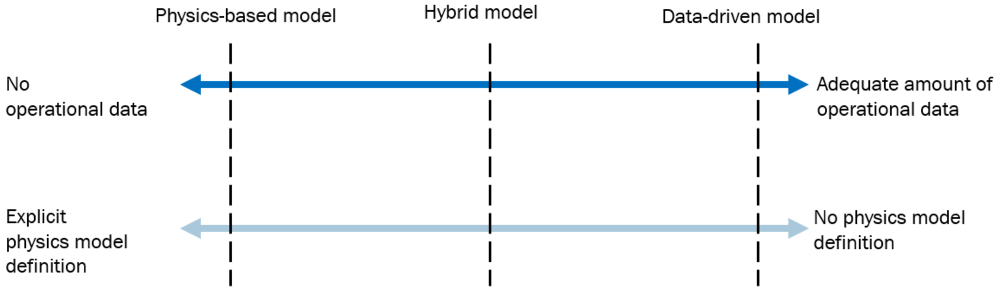

Figure 22 Model approach decided by the levels of data availability and physics model. Recreated based on [57]

In Table 1, hybrid model related references are listed for wind energy DT applications.

- Model Validation and Uncertainty Quantification

In wind energy industry, numerical tools are commonly used to assess the behaviour of complex dynamical wind turbine systems. These tools powerfully unite theoretical foundations, numerical models and experimental data which all include associated uncertainties and errors. It is the same for the models as part of DT. As DT is getting more maturely deployed, the model validation and uncertainty quantification will be mandatory exercises.

- Twin behavior

The DT should be synchronized at a specified frequency and fidelity to fulfill its specified purpose. The term real-time is used a lot, but to clarify it, for DT outputs, real-time is not always defined as the speed of blinking eyes. If a system has a response time of 10 minutes, then to provide results within 10 minutes is also real-time. For extreme loads monitoring, crack detection, emergency events etc., fast DT response time is needed. But for fatigue, routine maintenance plan, grid price monitoring etc., the DT response time can be much longer.

Fidelity is another important twin behavior of the models as part of DT. This needs efforts from all the elements: data, model and model validation and uncertainty quantification.

- Transdisciplinary and Systems modelling

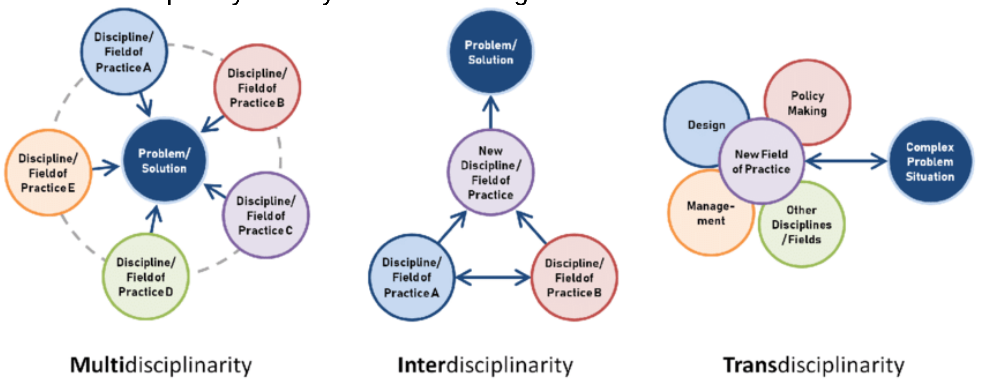

Figure 23 A comparison of multidisciplinary, interdisciplinary, and transdisciplinary approaches to innovation [58]

As the comparison shown in Figure 23: multidisciplinarity is one disciplinary view, supported by views from other fields of science; interdisciplinarity has many disciplinary views with equal weights; transdisciplinarity has multiple views in a common conceptual framework, joined by multiple stakeholders.

Wind energy research is rapidly changing, hyper-connected and is facing increasingly large-scale, complex and dynamic problem situations. So is DT as one wind energy digital solution. More recently, transdisciplinarity is increasingly relevant to innovators and entrepreneurs whose technologies or solutions are aimed at addressing complex societal problems. This larger-scale emphasis moves innovation beyond “customercentred” to a “society-centred” perspective, and it requires active collaboration with public and private sector organizations, governments, and communities [58].

When many different models are involved for a system in DT, the systems model is needed. Systems models are used to conceptually model the function, structure, behavior and views of a systems focused on specific profiles and perspectives to ensure an efficient view on the system[17]. Model-based Systems Engineering (MBSE) appeals a solution for transdisciplinary problems as elaborated in Chapter 4 for wind energy DT.

3.2 Summary

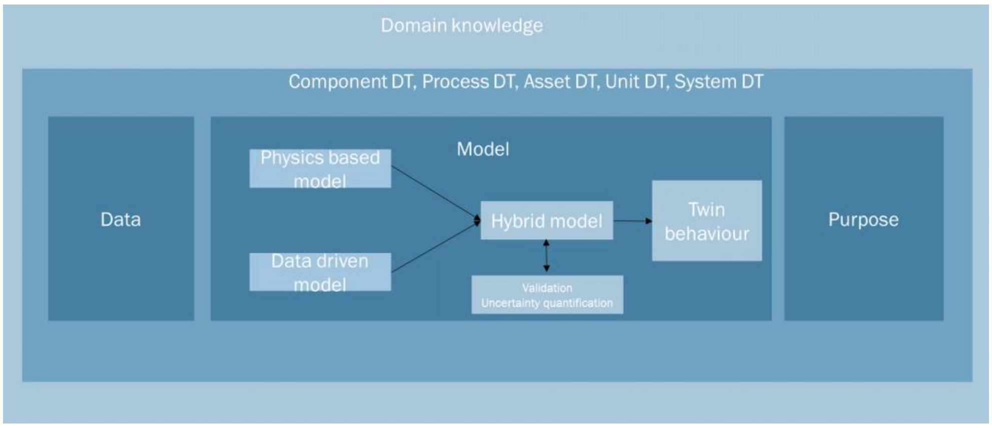

Figure 24 Wind energy DT elements governed by domain knowledge for different types of DT

As a summary, the wind energy DT is decomposed as elements listed in Figure 24.

[17] https://en.wikipedia.org/wiki/Systems_modeling

4 Full life cycle DT enabled by MBSE

DT is recognized as an effective approach to optimize interactively various activities in the entire product life cycle [59]. Systems Engineering (SE) is an approach to better understand a system, i.e. DT system in this report. Model-based systems engineering (MBSE) is a development in SE which is the formalized application of modelling to support system requirements, design, analysis, verification and validation activities, beginning in the conceptual design phase and continuing throughout development and later life cycle phases.

It should be noted that MBSE is different than Model Based Design. MBSE is the linkage of models to create a system that contains its boundaries, its contradictions, and can track the reasons for its design changes. It is the bridge between requirements and low-level high-fidelity technical models created by domain specialists. It also acts as the enabler for a wider DT to be implemented across the system lifecycle [60]. DT technology should be developed and deployed along the whole system lifecycle, together with MBSE all benefits can be realised.

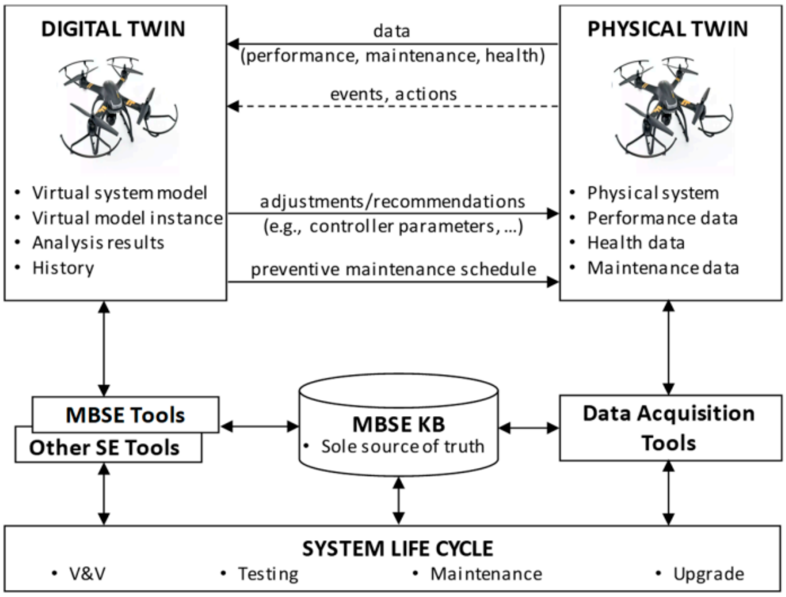

Figure 25 DT concept within MBSE framework [61]

The MBSE tools and other SE tools in Figure 25 include system modelling methods (e.g., SysML models, Design Structure Matrix, process dependency structure matrix, probabilistic models such as Partially-Observable Markov Decision Process (POMDP), discrete event simulation, agent-based simulation, model-based storytelling). The MBSE knowledge base constitutes the authoritative sources of truth, and system life cycle means systems engineering life cycle process models from validation & verification, testing, maintenance to upgrade [61].

Using an appropriate MBSE approach for DT, engineers can generate event-driven or agent-based simulations to explore the behaviour and interactions of the DT respectively. The benefits to both MBSE and DT can be strived for: system engineering modelling efforts are rewarded via the benefits of DT; the insights gained via DT provide valuable feedback to R&D and the development of DT is based on existing knowledge and not a costly hindsight activity [62].

5 Case study: ROM built with Ansys Static ROM Builder

In this case study, a static ROM (reduced order model) is built with a wind turbine blade FEM model where Ansys version 2022R1 is used.

5.1 Ansys Twin Builder

Ansys DT is a system level DT i.e. it contains variant multi-domain system modelers and it is able to provide system level solutions. The Ansys DT platform contains three parts: build, validate and deploy.

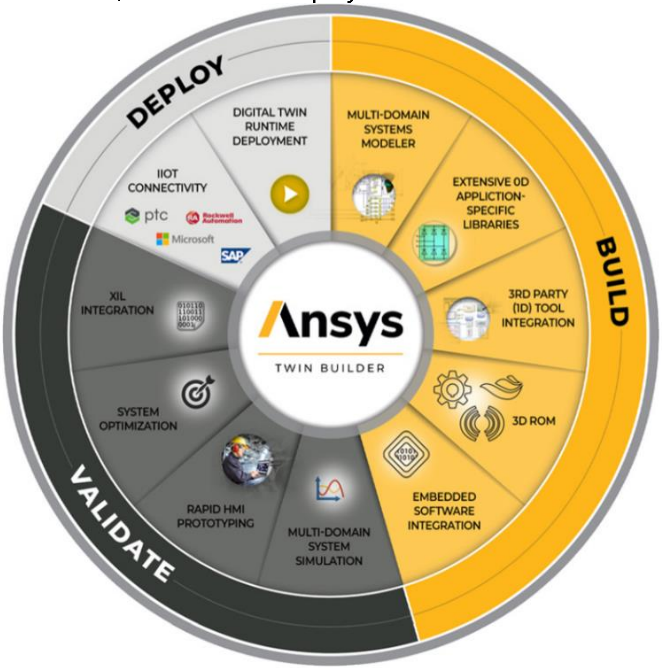

Figure 26 Ansys Twin Builder

Ansys Twin Builder is a multi-technology software platform to build, validate and deploy DT. It is simulation based with hybrid analytics capability. It can be deployed for virtual sensors, what-if scenario study, anomaly detection, root-cause analysis and failure mode prediction.

ROM is one of the key components of Ansys Twin Builder. ROM offers a mathematical representation for computationally inexpensive, real-time analysis. ROM is not only applicable to DT, it can also be used independently for design exploration, co-simulation with other physics-based models.

Ansys ROMs can be built up using the simulation results from different 3D simulations. Depending on the types of 3D simulation, different ROM techniques are used i.e. static, transient, linear or non-linear. A list of those ROMs is shown in Figure 27. The theories behind those different ROM types can be found in Ansys help documents. In Ansys version 2022R1, only Static ROM Builder and Dynamic ROM Builder can use 3D inputs and give 3D outputs.

ROM type	Parametric	Time varying	Non-linear	Input	Output
Response surface	x		x	scalar	scalar
Static ROM Builder	x		x	scalar/field	scalar/field
State space (LTI*)		x		scalar	scalar/field
State space (LPV*)	x	x	x	scalar	scalar/field
Dynamic ROM Builder		x	x	scalar/field	scalar/field

Figure 27 ROM types in Ansys Twin Builder 2022R1 (LTI: Linear Time Invariant; LPV: Linear Parameter Varying)

5.2 Blade FEM Model

The Ansys blade FEM model is built with shell elements and all the composite properties are defined. The blade FEM model has 60108 nodes and 61092 elements. The geometry and structure details of this FEM model are not relevant as it is only used here for demonstration purpose.

As shown in Figure 28, the blade root (location A) is fixed and a section force is applied at location B in flap wise direction.

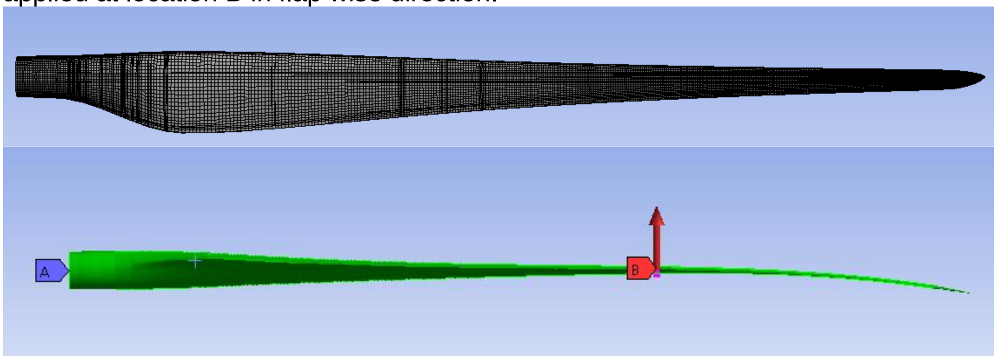

Figure 28 Blade FEM model

5.3 Static ROM Builder

MODEL: Nonlinear 3D blade model with shell elements
INPUT: section forces applied
OUTPUT: deformation field on the whole surface

Steps:
1. Prepare Mechanical simulation model in Ansys Mechanical
2. Define input and output parameters and set-up design points (32 design points for different section forces ranging from 500N to 8500N)

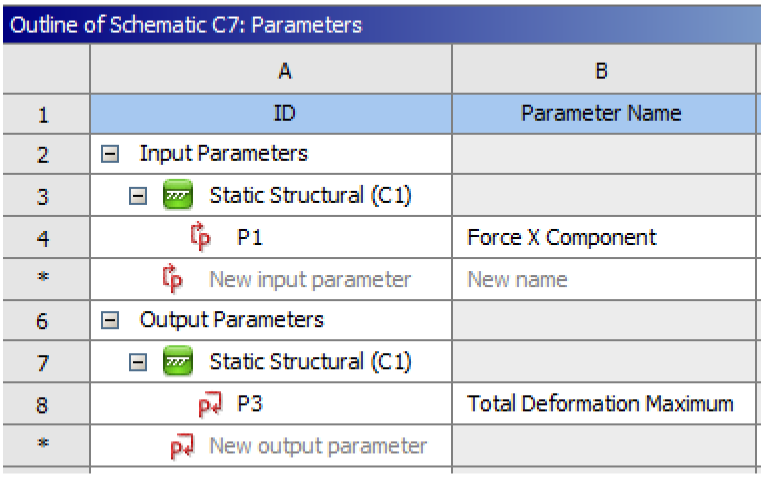

Figure 29 Define input and output parameters

3. Generate data for Static ROM Builder[18]

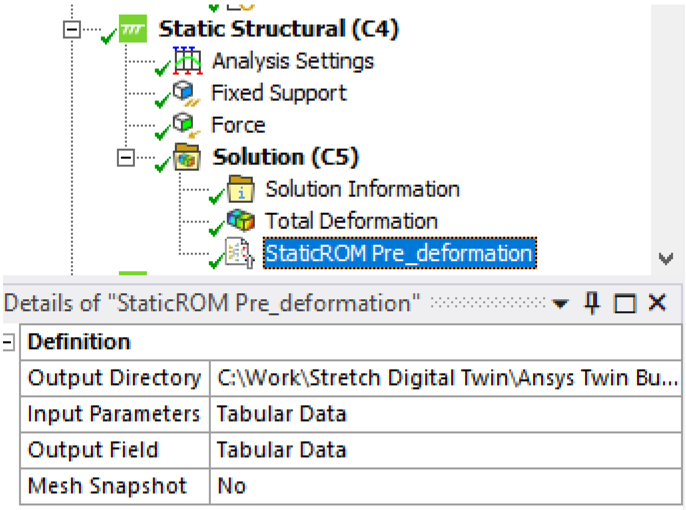

Figure 30 Using Mechanical add-on to structure the ROM inputs

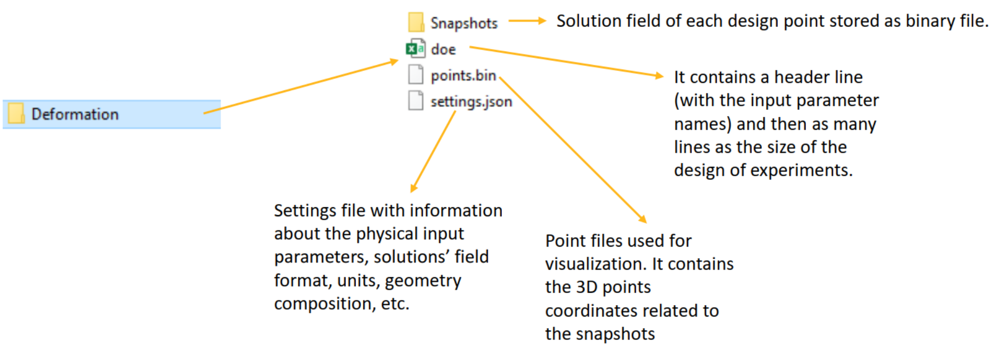

Figure 31 Generated data inside solver folder

4. ROM building using Static ROM Builder

[18] Ansys add-on called 'Static ROM Preprocessing for Mechanical' is needed for generating data directly from Mechanical. It is a handy tool to structure the ROM inputs

Static ROM Builder is inside the Ansys Twin Builder software package. The data generated from previous step are imported into Ansys Twin Builder (Figure 32) to build the ROM.

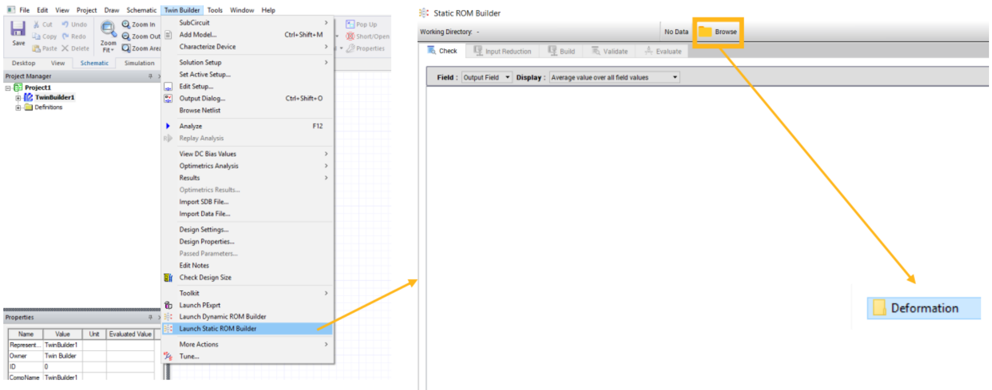

Figure 32 Launch Static ROM builder and select the folder prepared from previous step

The first step in Static ROM Builder is to check the data, e.g. average values, min and max values etc. An overview of min and max from all the design points (also called snapshots in Ansys) can be seen as in Figure 33. Each design point can also be checked visually here.

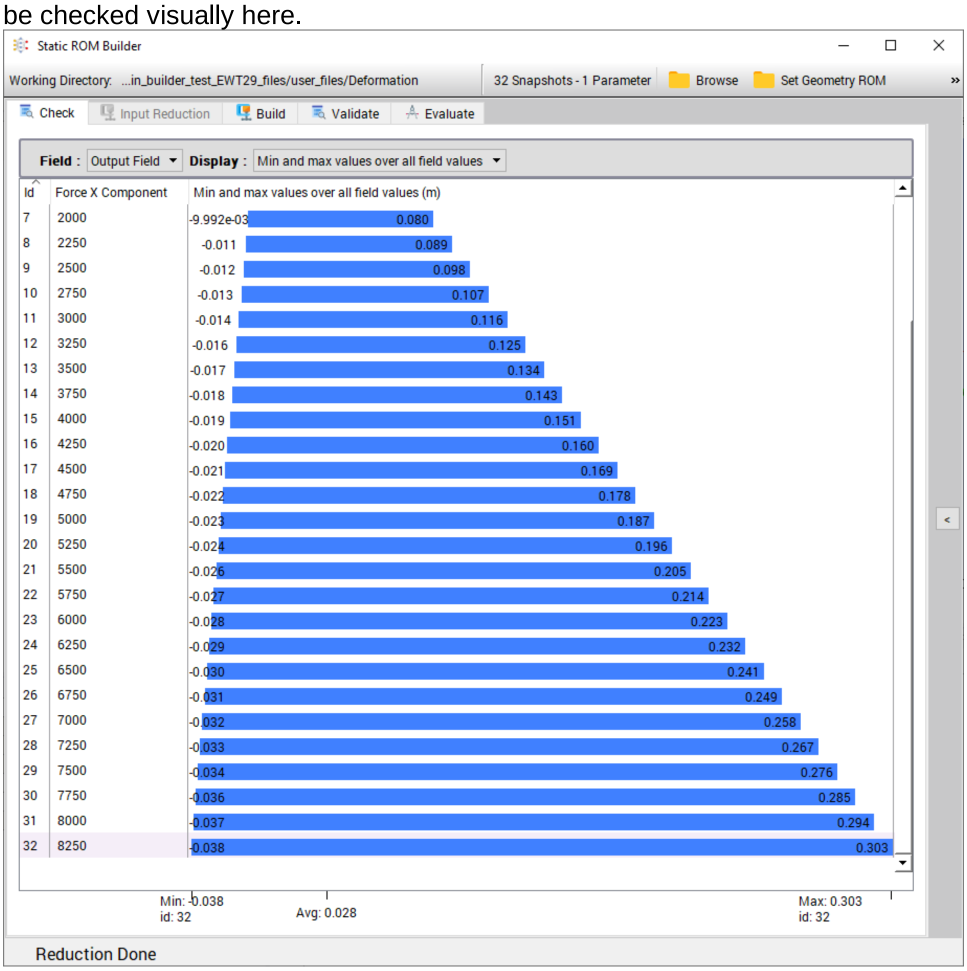

Figure 33 Check results from all design points

After visually checking the data, next step is to learn from the data for building the ROM. By default 50% of the snapshots are used for the learning phase. The program will automatically select the subset which is optimally distributed across the parameter space.

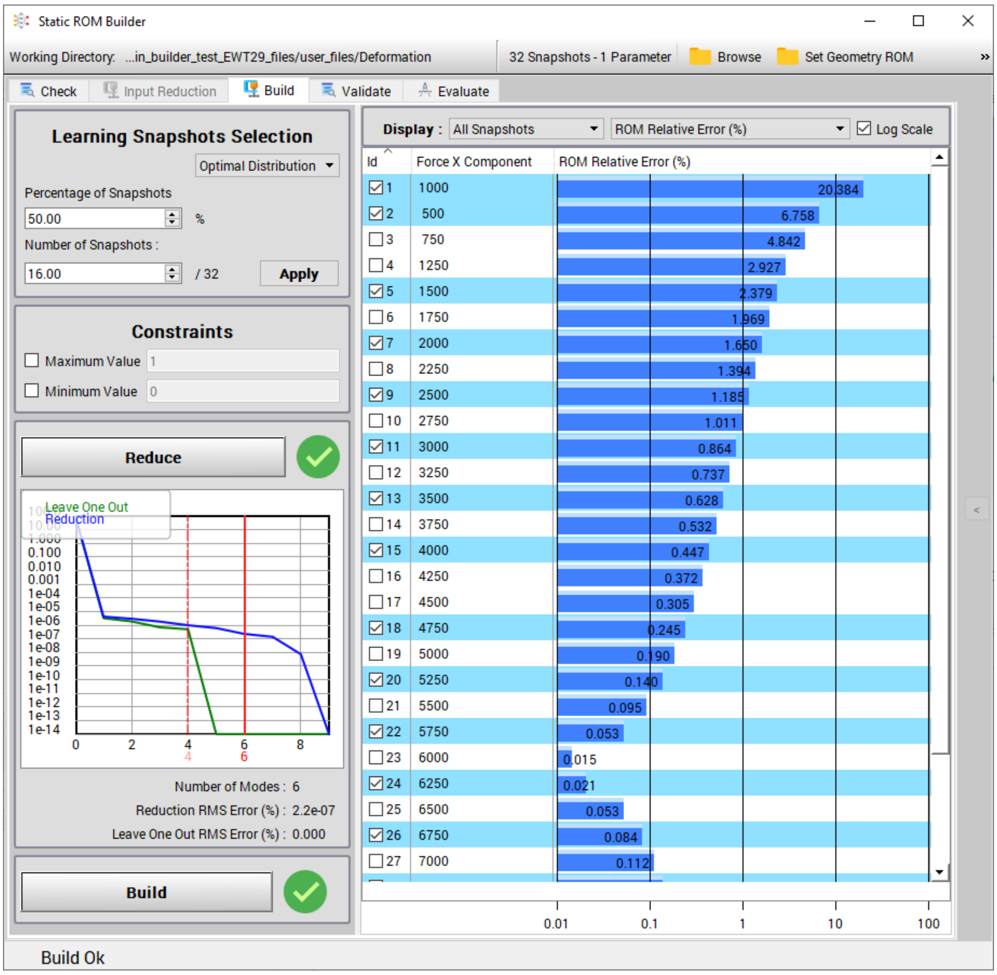

Figure 34 Building phase using default settings

If using all the 32 snapshots (100%), the ROM relative error decreases further except for snapshot number 1 as shown in Figure 35. The reason why snapshot number 1 has large errors is not found with limited time. The author of this report hopes to have more time to further investigate it in future.

On the left conner in the figure, the blue curve is the reduction curve which represents the accuracy of snapshot reconstruction with respect to the learning subset while the green curve (Leave One Out curve) represents this accuracy with respect to snapshots outside the learning set. Both curves are given as a function of the number of modes included in the basis of modes. Based on these curves and more precisely on the point where the two curves start to diverge, an optimal number of modes can be proposed.

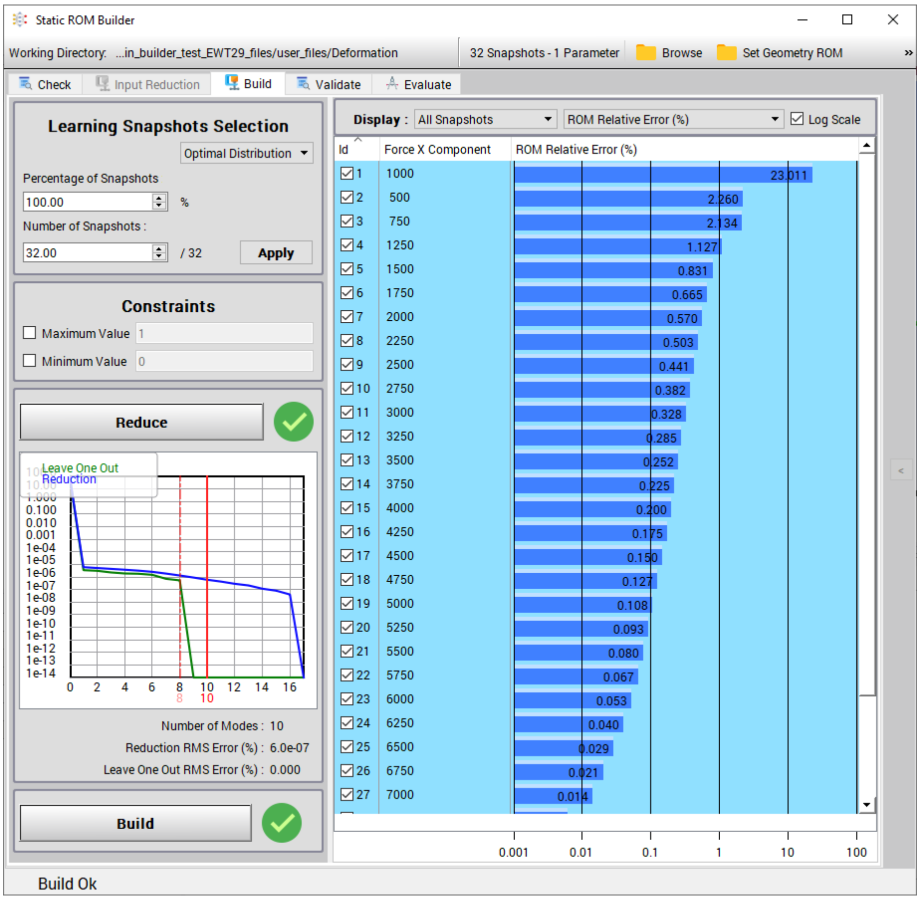

Figure 35 Building ROM using all the snapshots with 100% snapshots

Once the accuracy of the ROM on both the learning and the validation scenarios is satisfied, the ROM can be exported for a later usage in Twin Builder.

For each snapshot, a visual comparison with the 3D solver solution (Reference) can also be done. The field difference between the Reference and the ROM field is shown too in Figure 36 and Figure 37 from snapshot with 1000N and 500N respectively.

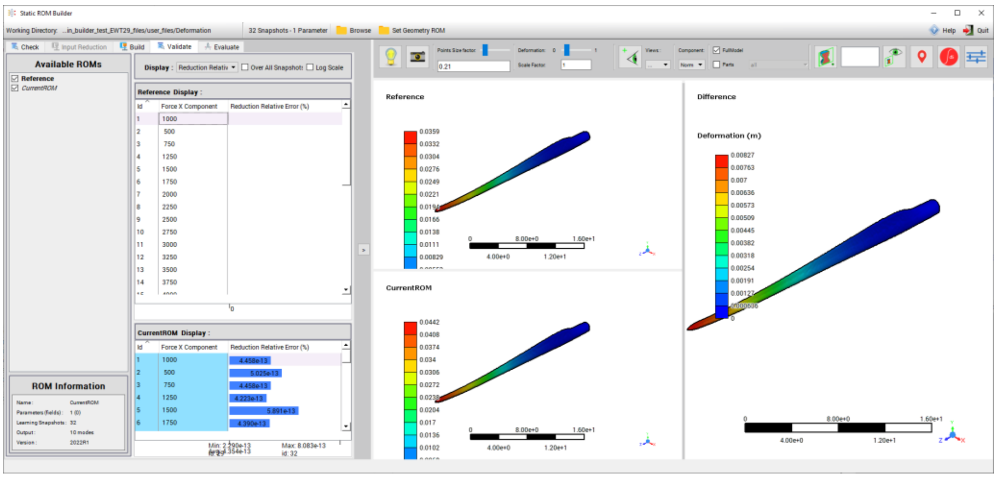

Figure 36 Validating ROM – snapshot nr.1

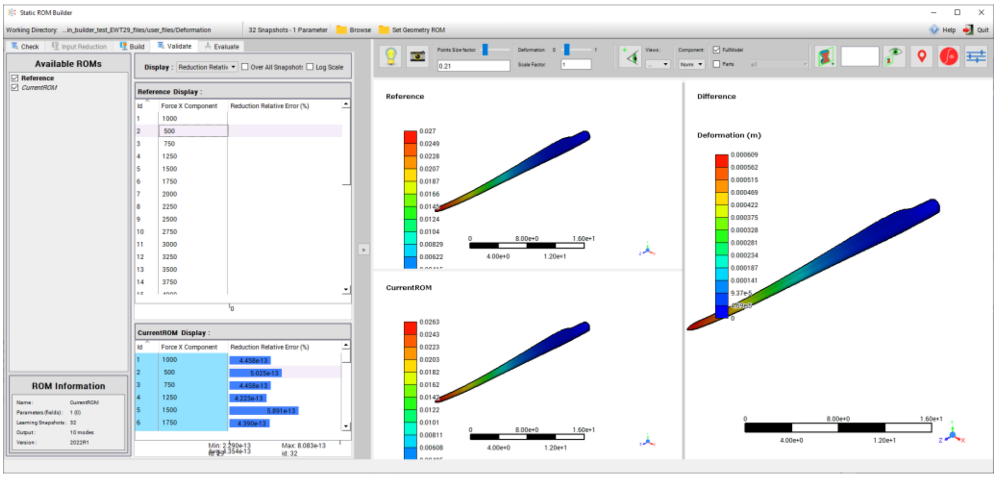

Figure 37 Validating ROM – snapshot nr. 2

In evaluating phase, for any given values of input parameters within the parametric range of the experiment, the selected ROM output displays in real time in the viewer.

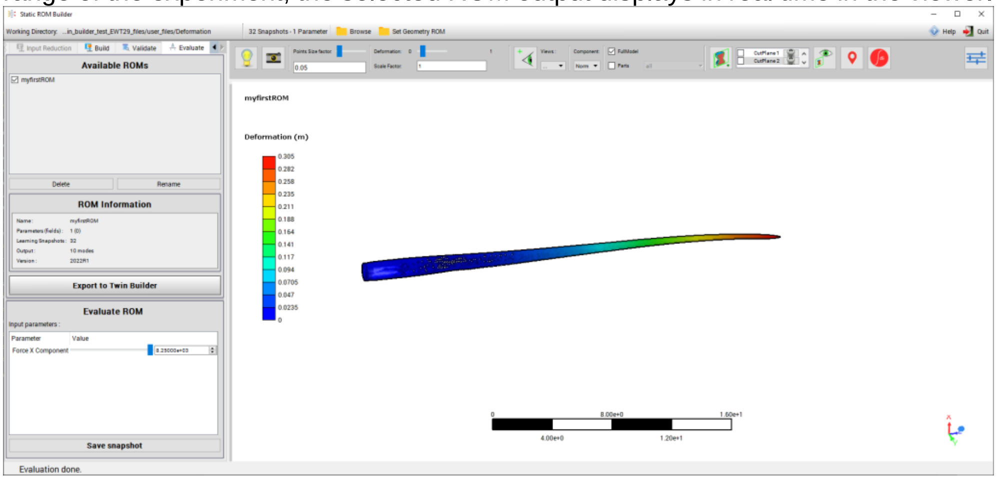

Figure 38 Evaluating ROM

After saving the ROM, it can be exported to Twin Builder. By default, only globalization operations are exposed as output of the ROM: min, max and average values over the 3D field described by the ROM.

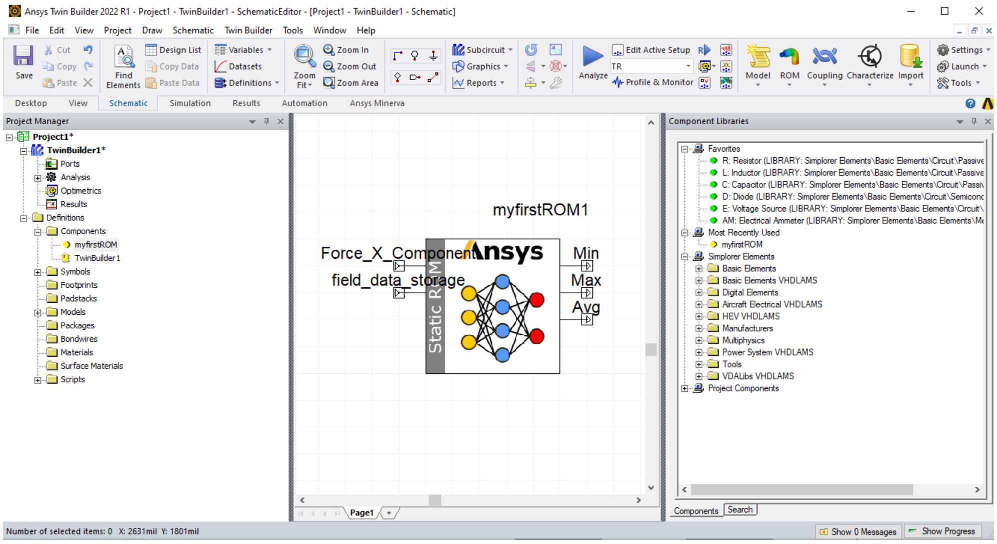

Figure 39 ROM exported to Twin Builder

In this study case, the ROM is saved and it is 14MB. The Ansys result file from one design point is 240MB, and this ROM is built from 32 design points, but with deformation as output only. Huge reduction of file size is a very promising advantage of using ROM to build DT.

5.4 Conclusions and recommendations

The ROM can replace the high fidelity FEA blade model to achieve fast simulation and realtime monitoring. In this study, only static ROM is built with displacement as output. Because of limited time and bugdet, the static ROM with stress or strain as outputs are not studied. This ROM can be further developed for the applications such as virtual sensors, virtual testing, what-if scenario study, root-cause analysis and failure model prediction etc.

The limitation of static ROM is that it does not contain the mass and damping matrix so the acceleration and velocity of the system can not be captured. For wind turbine applications, it will be more interested to develop dynamic ROM. This is the recommendation for the future works.

6 Case study: Rotor test rig DT built with Akselos model and verified by Ansys model

This case study is done together with GE in the STRETCH project. The study aims to get a working Akselos model as the rotor rig DT and correlate the rotor test rig measurements to the Akselos DT results. Using these findings, this chapter reports on the potential of using Akselos DT in test preparation and execution.

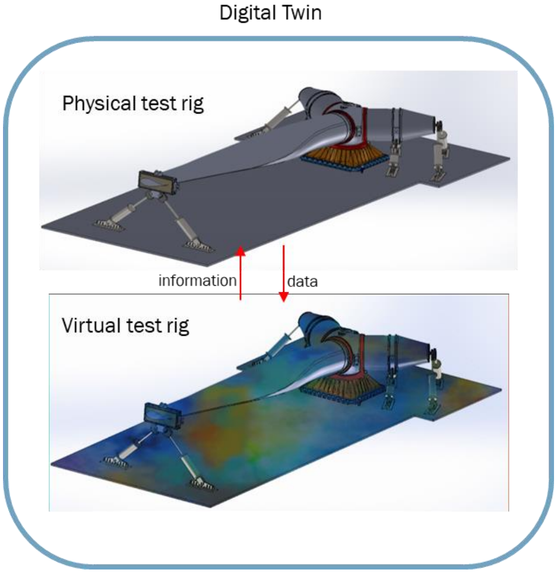

Figure 40 Test rig DT concept illustration

The test rig DT concept is illustrated as in Figure 40. The physical test rig represents all the measurements, tests and all the physical properties from the test rig. The virtual test right represents all the direct or derived simulation results from Ansys or Akselos models.

6.1 Rotor test rig

The rotor test rig is newly built at LM WMC as shown in Figure 41. The rotor test rig will allow for verification of the strength and the dynamic behaviour of wind turbine rotors under the enormous mechanical loads caused by large blades. It will be able to verify in-house the pitch bearings and pitch system that connect the wind turbine blades to the hub and allow pitching blades maximizing captured energy while reducing loads on wind turbine.

Figure 41 3D illustration of rotor test rig in STRETCH project © LM Wind Power

The test rig will simulate the simultaneous loads transferred from the three blade axis as in the real wind turbine operating condition.

The test rig is built to test the pitch bearing, hub and blade root connection, which are all critical wind turbine components. Testing them alone cannot mimic the real loading situation during wind turbine operation. Hence the test rig is built with all the necessary companion components i.e. loads transferring components (aft/fore blade load application systems, composite tube, truncated blade adapter and hub support as shown in Figure 42).

6.2 Ansys model

6.2.1 Test rig Ansys basic global model

In order to check the companion components, i.e. loads transferring components (aft/fore blade load application systems, composite tube, truncated blade adapter and hub support as shown in Figure 42), a basic model is made where the pitch bearing, bolt connections and hub are all simplified.

The truncated blade adapter and composite tubes are designed to represent the stiffness from real blades. All the material properties are modelled to align with the real test rig properties.

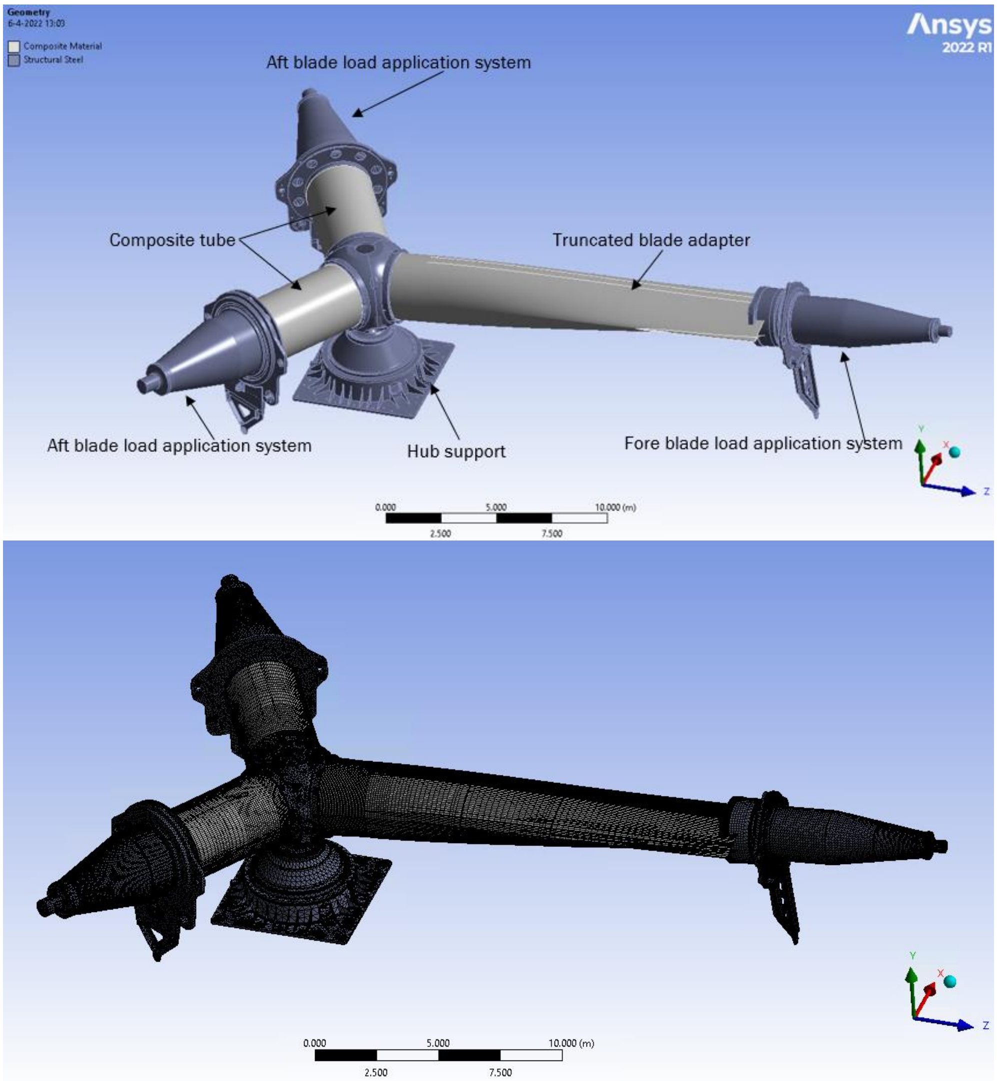

Figure 42 Test rig Ansys basic global model

The truncated blade adapter and composite tubes are modelled with shell element. All other components are modelled with solid elements. This FEM model contains 2,511,672 nodes and 1,555,970 elements. All the connections are bonded connection. The test rig support bottom is fixed in all degrees of freedom to the ground.

At last, Modal analysis is done using this basic global model to check the integrity of the model. The first 6 modes are calculated. The results are shown in Figure 43 where the 1st mode shape is displayed and the first 6 frequencies are listed on the bottom right of the figure. Those results could be checked with measurements but unfortunately not available during the period of this project.

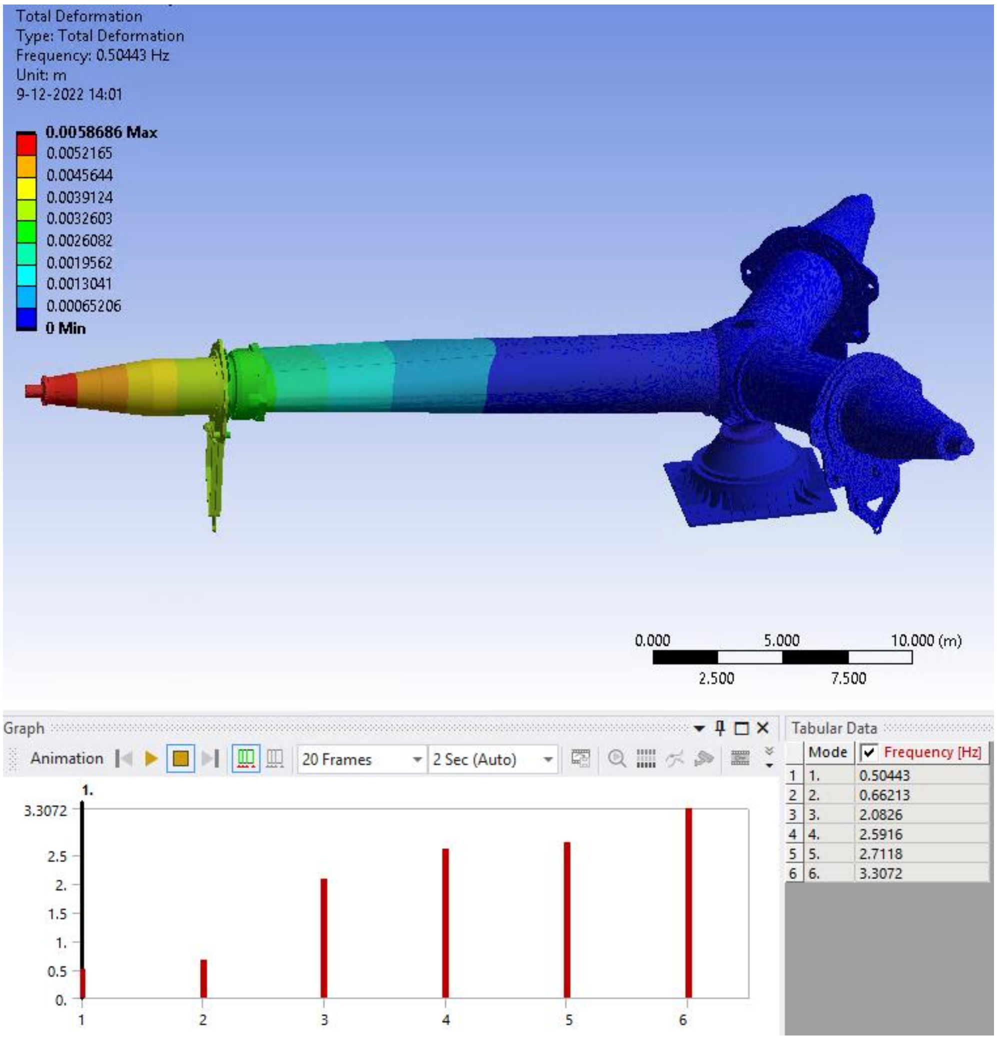

Figure 43 Modal analysis results

6.3 Akselos model

6.3.1 Introduction and work flow

Akselos engineering simulation software [63] is a FEA (Finite Element Analysis) tool based on reduced order modelling. It enables fast simulations of large and complex parametrized systems. The two main ingredients to achieve this are:

1. The Reduced Basis (RB) Method, a powerful model order reduction technique for parameterized partial differential equations (PDEs), and
2. A component-based approach, which enables engineers to create large, reusable, and reconfigurable models in an efficient manner

The combination of these two ingredients provides a new modelling framework that accelerates conventional FEA, and Akselos refers this framework as RB-FEA.

The RB method is one of the classic Model Order Reduction techniques. It reduces the computational complexity of mathematical models in numerical simulations. But it still has limited capability to solve large scale problem and large amount of parameters. It also requires continuous geometric parametrizations, e.g. it cannot introduce topological changes like removing a part or creating a hole. To address these limitations, the component-based formulation of the RB method was developed, e.g. the RB-FEA used by Akselos.

The key idea of RB-FEA is to create RB models for components, and connect components together to form large parametrized models, i.e. RB-FEA is built upon RB and uses components in a manner similar to how FEA uses elements as illustrated in Figure 44.

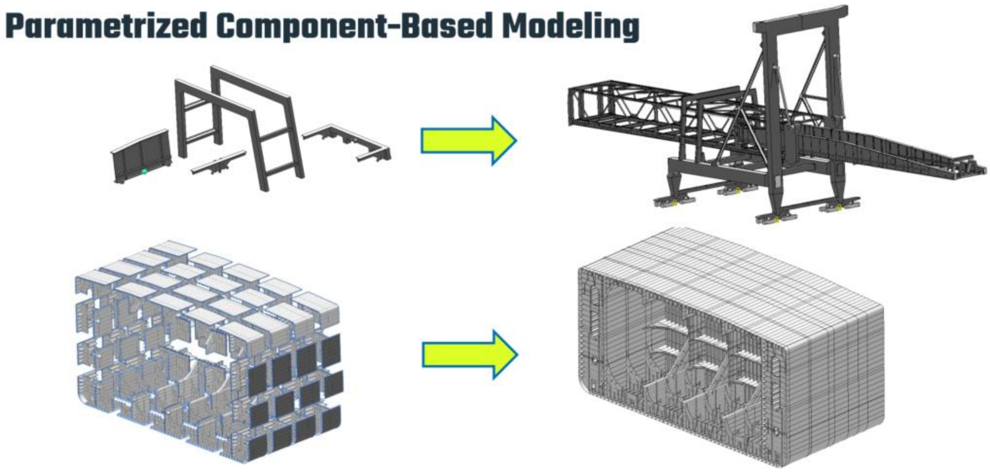

Figure 44 Parametrized component-based modelling from Akselos training document

With RB-FEA, one typically reaches 1000x speedup or more compared to conventional FEA for large-scale models as claimed by Akselos. A major limitation of RB-FEA is that it is inherently restricted to linear analysis since the elimination of component interior degrees of freedom relies on linearity of the PDE. To resolve this issue, Akselos has developed a framework that provides a tight coupling between conventional FEA and RB-FEA as shown in Figure 45. This means that it can use RB-FEA in “linear regions,” and conventional FEA in “nonlinear regions.” This process is done by ‘marking’ a component as linear or nonlinear before solving.

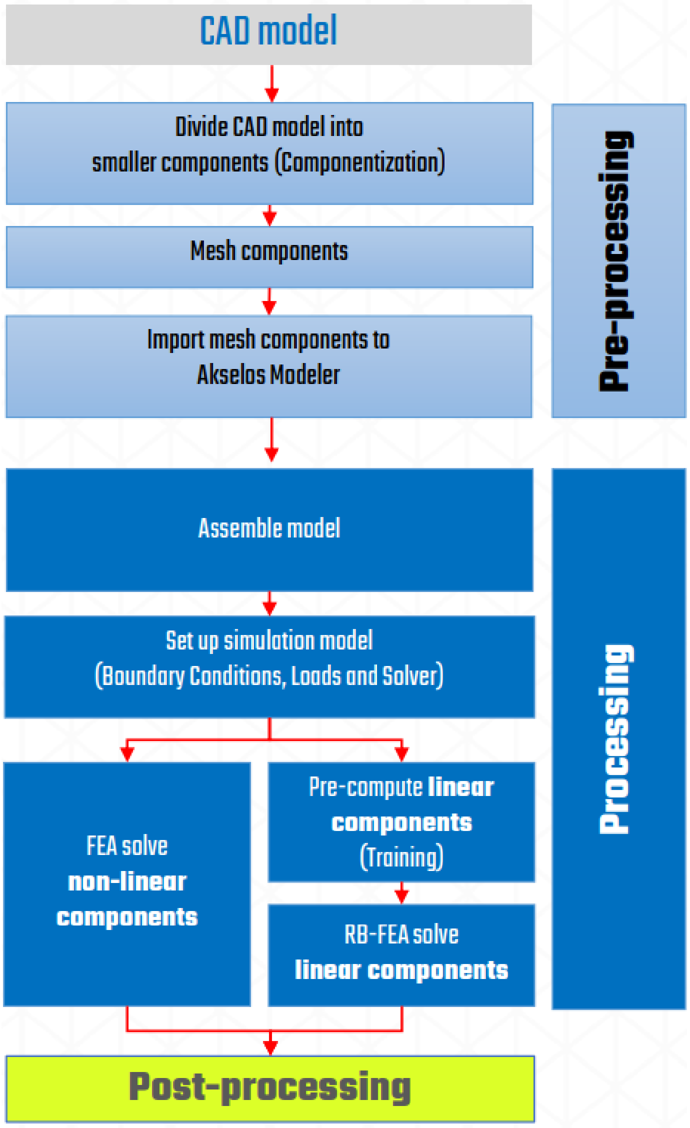

Figure 45 Akselos simulation workflow from Akselos training document

6.3.2 *Test rig Akselos basic global model*

6.3.2.1 *Introduction*

The test rig is a very complex and heavy model. As part of the initial DT framework, a basic global model is prepared first to explore the ways of modelling it in Akselos software. At the end, a lot of useful Pyhton scripts are developed to automate the modelling works.

This basic global model consists of hub, three pitch bearings, bolt connections between pitch bearing inner ring and hub, bolt connections between pitch bearing external ring and blade root. The load application systems from the test rig are not modelled. All the three blade roots (which are connected to pitch bearing inner ring) are modelled with simple composite tubes. The hub support is simplified too. Only the bolt connections in one blade are modelled, the other two blades have bonded connections.

6.3.2.2 Modelling

6.3.2.2.1 Componentization & Meshing

Following the procedures as illustrated in Figure 45, the CAD model first is divided into big components (using SpaceClaim) then meshed and further divided into 40 small components as shown in Figure 46 (using Cubit).

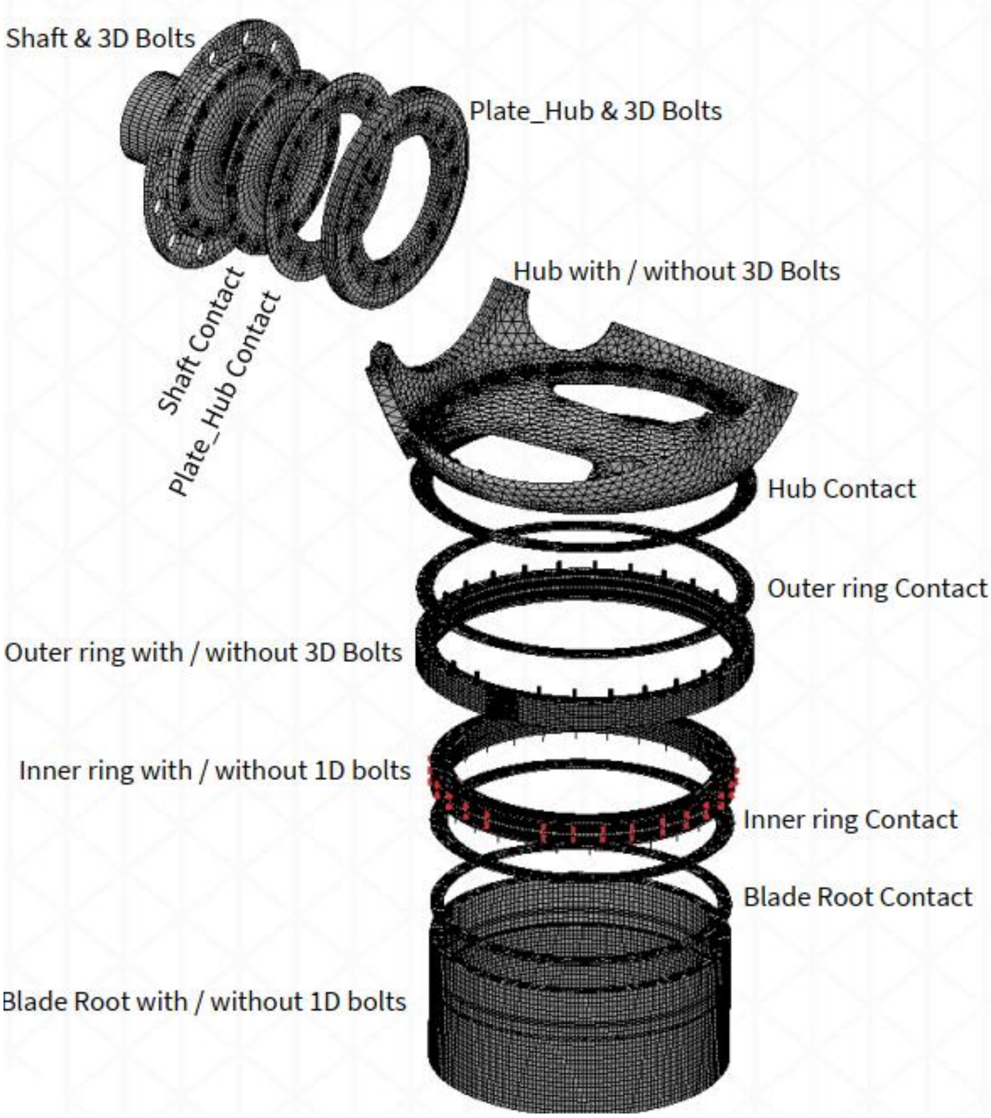

Figure 46 40 meshed components

The joint faces between the components are called face port. The contact face (frictional or bonded contacts) should not overlap with any face port. This is an unique requirement in Akselos modelling. It is important to note that the linear components (RB-FEA components) and non-linear components (FE components) are modelled separately. This is illustrated in Figure 47. A split plane is made close to the contact face between hub and bearing. The component on the left side of this split plane forms the RB-FEA component, the component on the right side forms the FE component.

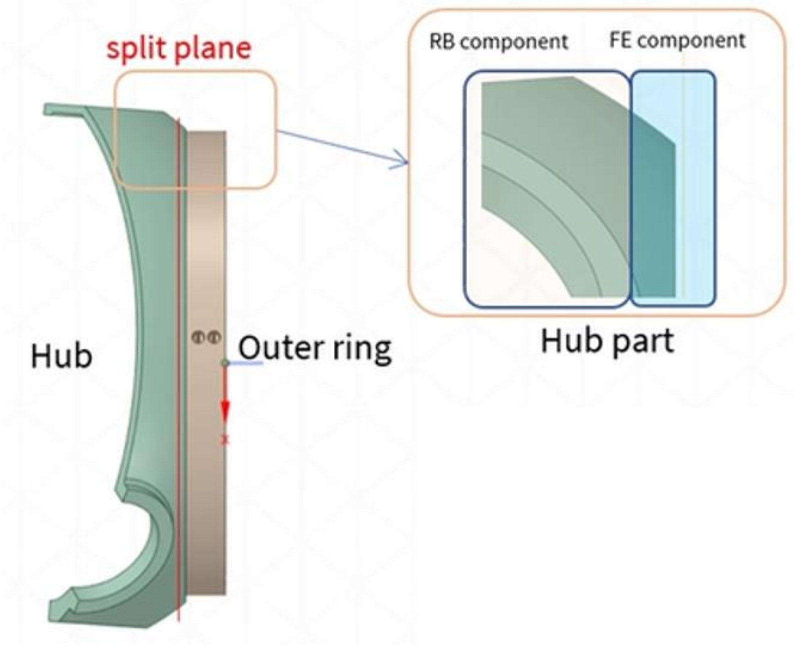

Figure 47 Split plane to separate RB-FEA component and FE component

The balls between the bearing inner ring and outer ring are modelled with compression-only 1D spring elements. The bolt between blade root and bearing inner ring is modelled with 1D beam element. The bolt between hub and bearing outer ring, between hub and shaft are modeller with 3D solid element.

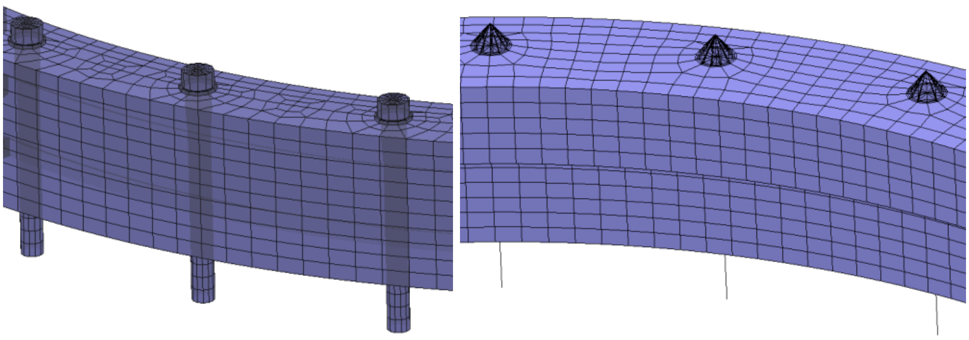

Figure 48 3D bolt (left) and 1D bolt (right)

6.3.2.2.2 Assemble & Set up model

The 40 meshed components in Figure 46 are imported and assembled in Akselos Modeler (version 4.7.16) to set up the final model as shown in Figure 49. In this step, the 1D bolt connections are created, the spring connectors (non-compressional beam element) between outer and inner rings are created, the one third hub and one blade are cloned to other two locations, the contact connections are also created, the boundary condition is defined (fixed support) and the orthotropic material properties are defined. Finally the load types and load cases are defined and the model is ready for the next step: training.

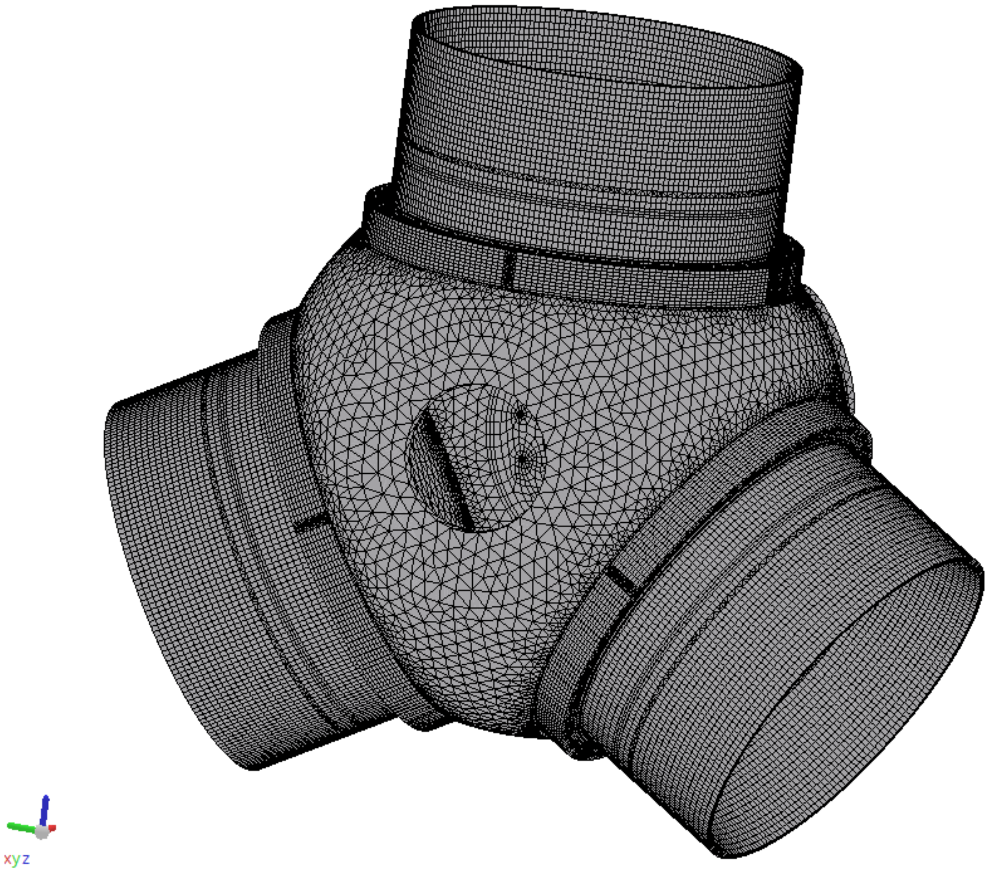

Figure 49 Assembled rotor model in Akselos Modeler

The number of DOF (degree of freedom) of the FE components (non-linear components) is about 13% of the full model. The other 87% is from linear components.

6.3.2.2.3 *Training*

Training is a critical step in Akselos Modeler which makes Akselos different than other traditional FEA software.

All the linear components will be trained for RB-FEA purpose. The linear components will be solved using RB-FEA solver and the non-linear components will be solved using FEA solver, i.e. the hybrid solver named in Akselos Modeler.

The training can be done on three levels: local submodels, global submodels and global model. The first two are for large scale models. The training time also increases from local submodels, global submdels to global model. The basic model here is not considered as a large scale model so the training on global model level is performed.

13 load cases are used to train the components. Those are:
- Pitch bearing bolt pretention load
- Blade 1 +/- My and +/- Mz

- Blade 2 +/- My and +/- Mz
- Blade 3 +/- My and +/- Mz

6.3.2.2.4 Solving

Both hybrid solver and FEA solver are used separately to solve load case 2 in order to get an impression about how the hybrid solver performs. All the plots in Figure 50 have the same lengend qirh 15 levles. It can be seen that the results have very tiny and negligible differences. The hybrid solver takes 442 seconds which is almost half of the calculation time with FEA solver. For a FEA model with 597391 nodes and 723737 elements, the hybrid solver calculation time is pretty fast.

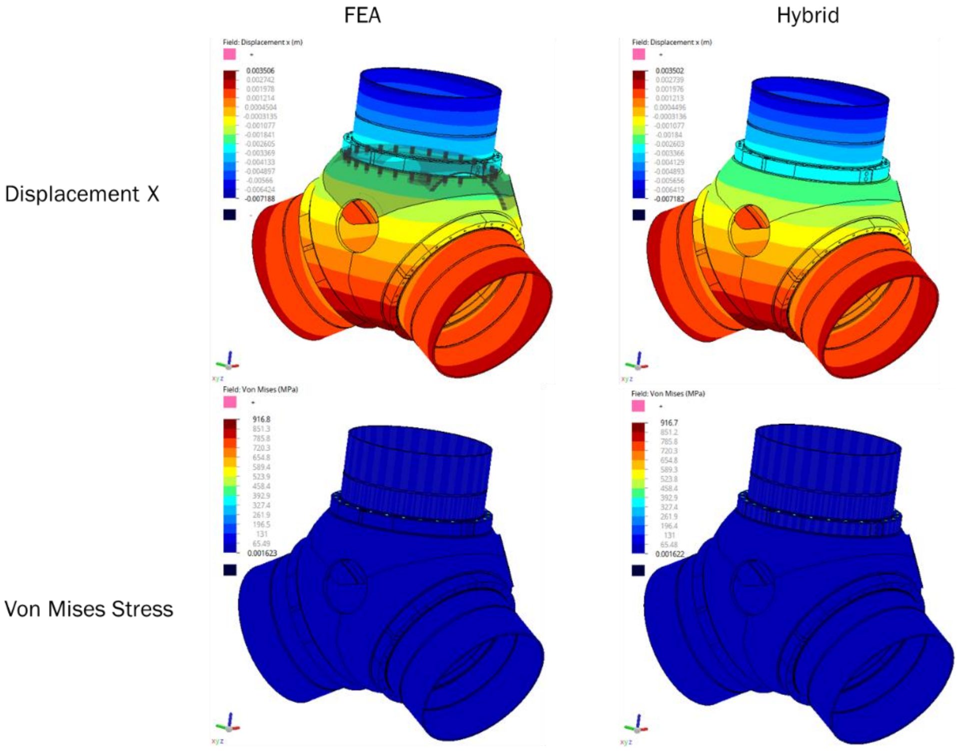

Figure 50 Results from FEA solver and Hybrid solver

6.4 Validation of Digital Twin with test results

The Digital Twin modelling was validated by comparing model predictions with results from Rotor model validation tests. 14 rotor static tests are are selected as load cases for the FEM calculations.

The Ansys basic global model as described in section 6.2.1 is used to run those load cases. The FEM calculations are run using Ansys nonlinear solver with large deformation on.

Strain gauges are instrumented on the hub surface to measure the local strains [64]. The measurements from 6 rectangular rosette strain gauges are selected (whose locations are easier to be identified in the FEM model) to compare with Ansys results.

The measured values from rectangular Rosettes are used to calculate the Von Mises stress which have been compared with Ansys results. Since the strains are not zero at the initial time, the initial strains are subtracted during post processing. Von Mises stress is a good equivalent stress to represent the distortion of a material, hence it is used to check the global response of the hub at different loadings.

Note: Because of confidential classification, all the detailed test specifications, test instrumentations and results from tests and simulations are reported in the STRETCH final report for RVO [64].

It is concluded that the stresses for some load cases match quite well but for other load cases there are significant differences. But as the FEA results are based on a simplified model, there are the following uncertainties from the model and those need to be addressed when calibrating the FEA model with measurements:

- All the connections are bonded, so the nonlinear loads transferring is not considered. This will result in different directional strain and stress locally.
- The mesh is quite coarse, so the local element strain and stress are not smooth.
- The pitch bearing model is simplified as coupled in all freedoms between inner ring and outer ring, so the non-linear loading paths are not captured in the model.
- Some strain gauges are also not fine-tuned as they give non-realistic values.
- The test rig uses complex kinematic models to apply the loads from the end of each axis, and it ends up with residual loads at the pitch bearing center.

The results from Akselos and Ansys for one load case are also compared. As expected, the results are visually quite different since the two models have quite some differences as explained in sections 6.2.1 and 6.3.2. Especially around the contact regions as the non-linear bolt connections and compression-only beams (to represent bearing balls) are modelled in the Akselos basic model but not in the Ansys basic model. It is concluded that both the two initial models in Ansys and Akselos need more iterations to improve in order to reach the same level of fidelity.

6.5 Conclusions and recommendations

The initial rotor test rig Digital Twin framework is set up as shown in Figure 51. The preliminary results are compared between Ansys and Akselos, and between Ansys and test results. Although the DT frame and models developed are in the initial phase, a lot of the values and potentials have been demonstrated:

- Using the physics-based Akselos model to solve complex models in short time ; this can be used to prepare large amount of high-fidelity simulation results for data-driven DT applications, such as developing a surrogate model.
- Using the physics-based Akselos model to solve linear FEA problems in (near) real-time.
- Correlate rotor test rig measurements with physics-based simulations results so the un-measured data can be obtained from simulation; detect if sensors aren't mounted or connected properly.
- Run the measurement test matrix in advance using numerical simulation to optimize the test plan; create effective test plans informed by simulation data; know when enough data has been captured.
- Using virtual testing as a good supplement to physical full-scale test to save physical resources, such as mistakes made, failed try-outs.

- Follow the life cycle of the rotor test rig and quickly identify and correct the drift in measurements.

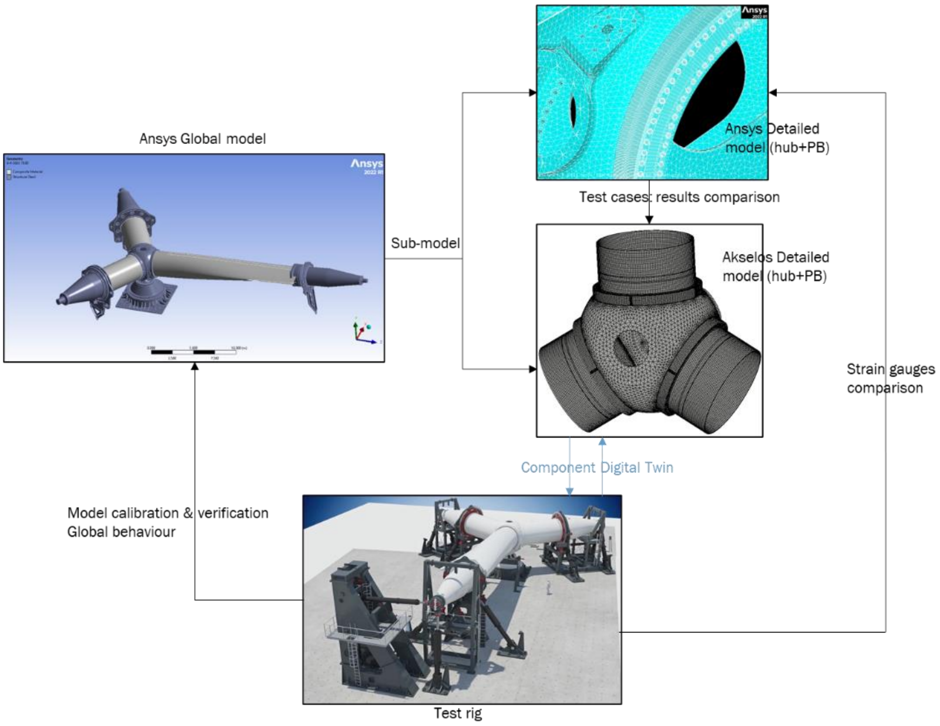

Figure 51 Rotor test rig Digital Twin framework

The verification between the physical test rig and the simulation model is a complex work. The tests performed so far are still limited. Moreover, because of many simplifications in this initial DT framework, the following recommendations are proposed for future works:

- The consistency between all the models and the physical test rig needs to be checked and confirmed.
- The Ansys model needs to be detailed to include the proper load transfer from pitch bearing inner ring to outer ring, and the hub mesh needs to be refined.
- The Ansys model needs to be verified with more test results to check and calibrate the model parameters; a detailed test plan should be made.
- The kinematic loading system of the test rig introduces residual loads in unwanted directions. Ansys could use rigid bodies to model this kinematic loading system to increase the model fidelity and match well with test conditions.
- With limited computation resources, the Ansys model takes about 60 minutes for calculating one load case, and the Akselos model takes 13 minutes for calculating one load case. Further efforts are needed to reduce the calculation time with more computation resources or optimizing the models (such as using sub-modelling or sub-structuring).
- IT/OT systems are needed to connect and synchronize the virtual test rig and physical test rig at a specified frequency to realize the DT values.
- A data management architect is needed to manage all the data and information from the virtual test rig and the physical test rig.

7 Conclusion

This report begins by reviewing the background information on digital twins and proposes aligning the understanding of digital twins using the definition from the Digital Twin Consortium: a digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity. Following this definition, the report reviews digital twin applications from the literature and in the wind energy industry. For the academic research of wind energy digital twins, a simple digital twin structure, as represented again in Figure 52, consisting of three elements - data, model, and purpose - is introduced. The understanding of hybrid model is also introduced, as represented again in Figure 53 and it is important to highlight the twin behaviour here as this distinguish digital twin models with other numerical models.

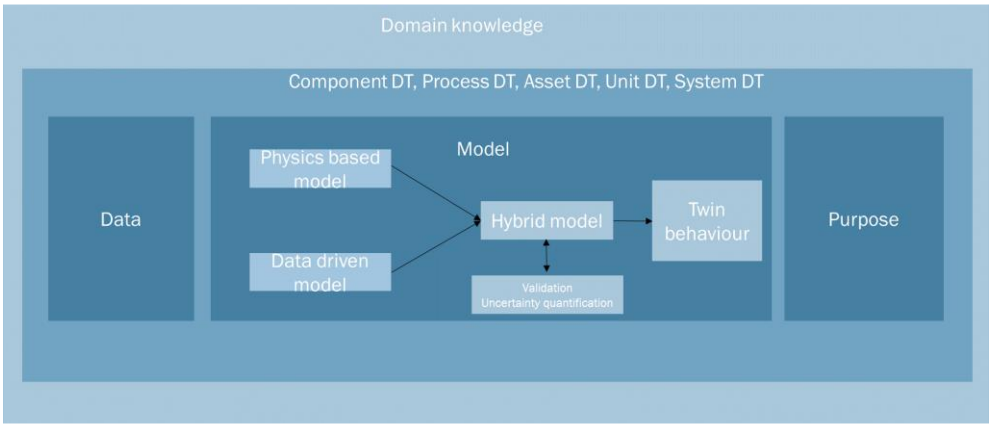

Figure 52 Wind energy DT elements governed by domain knowledge for different types of DT

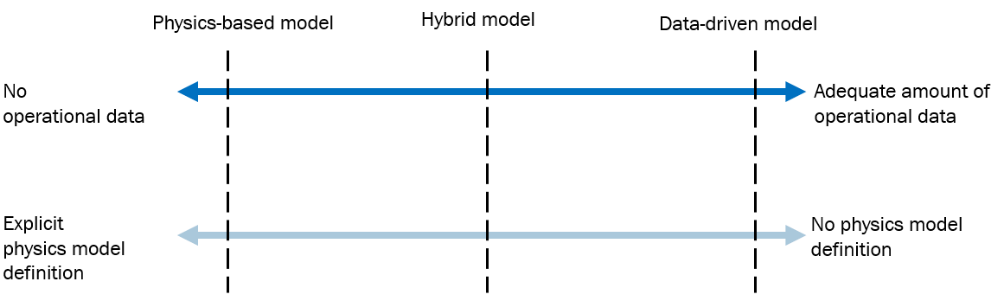

Figure 53 Model approach decided by the levels of data availability and physics model. Recreated based on [57]

To architect a digital twin capable of representing the entire lifecycle of real-world entities and processes, a systematic methodology is needed. Model-Based Systems Engineering is a suitable approach for this purpose and is briefly discussed in this report.

The two case studies demonstrate promising applications of wind energy digital twins. The first case study involves using Ansys Twin Builder to create a reduced-order model (ROM) of a wind turbine blade FEM model. This ROM can run within seconds while maintaining high fidelity. It can be deployed for virtual sensors, virtual testing, what-if scenario studies, root-cause analysis, and failure model prediction, among other applications. The second case study focuses on building a digital twin framework for the rotor test rig developed within the STRETCH project to test wind turbine pitch bearings and hubs. The digital twin is used to gain a better understanding of the behaviour, loading, and dynamics of the tested assembly to optimize test preparations, expedite test setup, and reduce risks and delays during testing. The results from the digital twin model of the rotor test rig, including test articles, are encouraging, although further work is required to enhance accuracy and practicality.

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