Proceedings of the ASME 2019 38th International Conference on Ocean, Offshore and Arctic Engineering OMAE2019
June 9-14, 2019, Glasgow, Scotland, UK

OMAE2019-95152

ON DIGITAL TWIN CONDITION MONITORING APPROACH FOR DRIVETRAINS IN MARINE APPLICATIONS

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ABSTRACT

A digital twin is a virtual representation of a system containing all information available on site. This paper presents condition monitoring of drivetrains in marine power transmission systems through digital twin approach. A literature review regarding current operations concerning maintenance approaches in todays practices are covered. State-of-the-art fault detection in drivetrains is discussed, founded in condition monitoring, data-based schemes and model-based approaches, and the digital twin approach is introduced. It is debated that a model-based approach utilizing a digital twin could be recommended for fault detection of drivetrains. By employing a digital twin, fault detection would be extended to relatively highly diagnostic and predictive maintenance programme, and operation and maintenance costs could be reduced. A holistic model system approach is considered, and methodologies of digital twin design are covered. A physical-based model rather than a data based model is considered, however there are no clear answer whereas which type is beneficial. That case is mostly answered by the amount of data available. Designing the model introduces several pitfalls depending on the relevant system, and the advantages, disadvantages and appropriate applications are discussed. For a drivetrain it is found that multi-body simulation is advised for the creation of a digital twin model. A digital twin of a simple drivetrain test rig is made, and different modelling approaches were implemented to investigate levels of accuracy. Reference values were derived empirically by attaching sensors to the drivetrain during operation in the test rig. Modelling with a low fidelity model showed high accuracy, however it would lack several modules required for it to be called a digital twin. The higher fidelity model showed that finding the stiffness parameter proves challenging, due to high stiffness sensitivity as the experimental modelling demonstrates.

Two industries that could have significant benefits from implementing digital twins are discussed; the offshore wind industry and shipping. Both have valuable assets, with reliability sensitive systems and high costs of downtime and maintenance. Regarding the shipping industry an industrial case study is done. Area of extra focus is operations of Ro- Ro (roll on-roll off) vessels. The vessels in the case study are managed by Wilhelmsen Ship Management and a discussion of the implementation of digital twins in this sector is comprised in this article.

INTRODUCTION

A digital twin is a virtual representation of a system containing all information available on site. This means that all descriptive condition information found on site are available in a digital model in a virtual and dynamic environment completely matching the real life of the system [1]. There is added value by utilizing a digital twin when the asset is of high value and is hard-to-access. High value assets are: *"technologically*

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intensive, expensive and reliability critical requiring continuous maintenance throughout their life cycle" [2].

Industries that are concerned with high value assets and remote locations are industries that can benefit largely on digital twins. Regarding two of these industries, offshore wind and shipping, they both have the drivetrain, gearbox and bearings in common. Operational and maintenance costs could be reduced by optimizing the maintenance strategy used. Improved maintenance strategies would contribute signicantly as these are components that lead to costly downtime. In the regards of creating a model-based condition based system, building and utilizing a digital twin could be beneficial and out-staging the data-driven condition monitoring by offering a holistic and predictive health monitoring. This paper will therefore consider the digital twin approach in these areas, focusing on the drivetrain in the two industries and discussing pitfalls and benefits and challenges, as well as exemplifying it with a digital twin model for a test-rig drive train.

Three different data analysis approaches for condition monitoring could be proposed; data-driven, model-driven and physics-based model-driven. The data-driven approach is sufficient in many cases, but for more complex and cost-heavy assets a model-approach have a more holistic monitoring scheme. The model-driven one collects the data and reaching sufficient amount of data, it is possible to run a machine learning algorithm on the sensor data, discovering trends and correlations without having the domain knowledge usually required for such an analysis [3]. However, even though one can discuss the correlation utilizing machine learning, there is a lack of causality, losing the effect of improving the operation of the system. Erikstad discusses these pros and cons [3]. Further in this paper a physics-based model approach will be focused on, as well as a proposed scheme of modelling with a test-rig drivetrain.

DIGITAL TWIN BACKGROUND

The concept of a digital twin was first introduced by the NASA Apollo programme and has evolved as the present technologies continues to grow. NASA started publicly using the term digital twin by calling it: *"(..) an integrated multiphysics, multiscale simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin"* [4]. Some, however, argue that a professor at University of Michigan, Michael Grieves, proposed the digital twin first under his executive course Product Lifecycle Management (PLM) at the university. There he defined it as a system comprising three components; a physical product in real space, virtual product in virtual space and the required interconnection between these two [5] [6]. General Electric has created an IoT Platform; Predix IoT. They denote digital twins as *dynamic digital models of physical assets and systems* [7]. Erikstad proposes that a digital twin is a *[..]model capable of rendering the state and behaviour of a unique real asset in (close to) real time.* [3]. Erikstad also suggest that referring to it as a twin is the wrong biological reference, and calling it a digital clone would be more correct as they are more close to being replicas of each other, than a twin is [3].

Erikstad further defines a digital twin as *"a digital model capable of rendering state and behaviour of a unique real asset in (close to) real time*. Erikstad also comprises five characteristics required for a digital twin; identity (making the twin as close to one-to-one cardinality), representation (capturing the assets data), state (get data in as close to real time as possible), behaviour (digital twin responding identically to external factors as the real asset, and context (describing the external factors like wind and waves that the real assets is experiencing [3].

BENEFITS

The digital twin would virtually be experiencing the same environment as the twin on site, and evolve identically through out the life cycle. This physical model type could be an answer to the issues raised with data-based systems as data interpreting would be done by the twin. Data pre-processing would also have to be done in this scheme, defined by the nature of the system. The assets would be considered as a whole, all components included and implied faults could be predicted as the twin will have life cycle updates [8]. It is then possible to schedule appropriate maintenance and reduce downtime and costs. Furthermore, it would be possible to retrieve sensor data from anywhere on the digital twin, opposed to the data from the real twin that is restricted to the location of the sensors. There is significant added value for a digital twin when implemented in assets of high value in hard-to-access locations for these reasons. As discussed, a drivetrain in an offshore wind turbine could be such an asset. Another asset could be the drivetrain in a Ro-Ro ship or other vessels that are sailing for longer distances.

An optimal digital twin, as described by Rosen et al., is comprising autonomy, modularity and connectivity. Autonomy is defined by Rosen et al. as *"Intelligent machines that execute high-level tasks without detailed programming and without human control"* [8]. All autonomy in this matter relies on an accurate virtual model, being the decision backdrop for actions and skills employed. Autonomy could be achieved with remote maintenance. This could be done by online collecting health data and executing software based tasks and upgrades to the physical asset.

The communication between the twins is enabled by the continued rise in connectivity [1]. Web technology is evolving, internet protocols and the rise of the of Internet of Things (IoT), which is the interconnection between objects, enhances intercommunication [9]. Rosen et al. suggest IoT in the following way: *"ubiquitous connectivity such as the Internet of Things facilitates closing of the digitalization loop, allowing next* *cycle of product design and production execution to be optimized for higher performance"* [8]. Data could be handled on an IoT platform, opening several opportunities for applications, making connectivity and data handling accessible. Summarizing and scoping the benefits found not comprised above, Fedem SAP AS has proposed the top ten most useful applications that a digital twin has, for high value and complex assets [10]:

1. Remaining life assessment of structure
2. Inspection/maintenance planning based on true load history
3. Relationship between loads and power production for control system policies
4. Early damage detection for pre-emptive maintenance and shutdown prevention
5. Hindsight to foresight access to (aggregated) time series for design feedback
6. Virtual inspection support
7. Predict consequences of (adverse) future operating conditions
8. Multi-asset orchestration/control and synchronization
9. Inspection/monitoring process support (cost reduction)
10. Visualization and inspection of stresses at inaccessible/hidden locations

CHALLENGES

Model

The digital twin of a drivetrain could be modelled and when including data acquired online from the on-site sensors, the condition of the drivetrain could be modelled. Where, and at what rate, the sensors would be collecting data could be based on what offshore wind turbine type, or what vessel, the drivetrain is located in, guidelines from class societies and ISO standards, and by considering the individual drivetrain hot spots for fatigue damage. Creating a sufficiently high-fidelity model will be a demanding issue and a general algorithm has yet to be made for fault diagnosis in a complete wind turbine [11] [6]. Altogether, designing a digital twin is not straight forward to do. A drivetrain both in a wind turbine or in a vessel is a complex system, containing several subsystems, external factors and it would require sophisticated design to be able to get an accurate twin, or clone.

Data

Optimally the digital twin would constitute all information about the physical system. The amount of data acquired would be of a substantial size and containing both unstructured and diverse information. Hence, the connectivity would cause an architectural challenge for such big data analyses [1] [12]. Anwer et al. proposed a concept of Skin Model Shapes for design and manufacturing phase [13]. This concept has been further conceptualized through other research and represents a digital and abstract model of the physical interface between an object and its environment and how to process data retrieved [14] [15]. However, this approach is more relevant for manufacturing and mass production precision. For a drivetrain in an offshore wind turbine or in a shipping vessel, the contact analysis is of higher relevance and could be done numerically in a model-based approach.

The digital twin could either be collecting data continuously or by intervals. If doing so continuously it might lead to excessive data. This could be exchanged with an assumption of the process being stationary and time independent for certain short time periods. Additionally, the whole drivetrain should not have to be implemented with sensors. This would be expensive and unpractical. A vulnerability map would aid in employing a sufficient amount of sensors, and their independent rate of monitoring [16]. It should also be discussed in what degree it is important to save data. By not saving it, there is less need for computational capital, however there could arise a need for historical data. When building a data driven digital twin, by performing machine learning, large amounts of data is required to train the machine learning algorithm. However, by using a physical-based model it is relieves the requirement for historical data and solves this issue [3].

Roy et al. discusses the effort that would have to be behind prognostics based on data from monitoring. The research debates a need for three components; confidence in accurate data, material degradation modelling and mastering the trade off between holistic overview and detail and precision [2].

Autonomy and Remote Maintenance

Roy et al. further discusses that to achieve a remote, autonomous operated maintenance scheme further maturing of the technology has to be achieved, addressing current challenges in autonomous maintenance [2]. There are significant benefits for employing autonomous and remote maintenance in drivetrains in offshore wind turbines, and the system would increase its availability if this is done well [17].

Furthermore, remote maintenance could be executed by utilizing remotely controlled robots [2]. In a vessel, wind turbine or other complex and remote systems they could be controlled autonomously, enabled by visualizing in a digital twin, and perform maintenance tasks. This would be very advantageous for offshore wind turbines due to the short weather windows open for access, and the robots could be permanently installed. Remotely controlled maintenance robots are already widely used in nuclear industry [18]. In some designs the fault diagnosis conclusion could be sent back to the system to achieve autonomous maintenance by the robot, for routine tasks. Looking even further, it could be possible to achieve a maintenance technician operating in the virtual model enabled by virtual reality technology [19].

Connectivity

Interconnecting the twin and sensors in an intelligent system by IoT have been researched by Xu et al., and three challenges were discovered. Firstly, there are issues with communicating the data from the IoT sensor network. Secondly, there will be issues with non-stationary and non-linear fault prediction. Lastly, there will be a vast amount of data to process [20]. IoT is enabling efficient maintenance, however there will still be a need for a fundamental expertise of degradation mechanisms and root causes [2].

A dynamic linkage between the twins is challenging to achieve accurately [20]. Sensor data being continuously transferred from real life to the digital twin are introducing data processing challenges. Both interconnecting well and smart with an offshore installation or vessel are of focus to achieve interaction, as is one of the digital twin premises [6].

Furthermore, issues raised with trusting a digitally interconnected system are present. If unwanted sources were able to control or even read data in a digital twin system, it is of essence to have a high standard protection system to both avoid this from happening and to restrict damage and being able to reverse the situation. A significant effort for cyber securing the data network will have to be of high priority [21].

INDUSTRIAL APPLICATIONS

To exemplify the need of digital twin two sectors will be highlighted in this paper, the offshore wind industry and the shipping industry. The shipping industry is represented by Wilhelmsen, one of the largest shipping companies in the industry today. These industries have in common their high value assets and hard-to-access location, making them ripe for digital twin potential.

OFFSHORE WIND INDUSTRY

Renewable energy in general, and wind energy specically, is increasing in capacity and is projected to continue to grow. With the expansion of wind turbines, an increased segment is found offshore. Moving from land based to offshore wind turbines, leads to more power extracted, less visual impact and less land displacement. However, new challenges arise, concerning technical issues and cost. There is an increased pressure to reduce costs where ever possible.

The main reasons for downtime in the offshore wind industry are drivetrain related and it would be of interest to monitor its health in a holistic way. Concerning a drivetrain in an offshore wind turbine, a digital twin for the drivetrain alone could be build. This is due to the logically permitted decoupled approach. Global forces will have to be of importance nevertheless, however excitation to resonance is unlikely from global forces [22]. Starting with a global model and analysis, the loading on the drivetrain could be obtained and by the detailed model gear loads and load response analysis will be performed simultaneously to get instant conditions. Fedem Technology (SAP SE), a Trondheim based software company, has developed a digital twin and has it operating with several systems, e.g. offshore wind turbines in the north of Norway. Figure 1 shows how the physical system "twins" with the digital representation through intercommunicating with online sensor condition monitoring. An external load on the wind turbine is represented in the digital twin through an actuator and virtual sensors [23]. The data is collected and has to be pre-processed before treated by the twin. After the twin has evaluated it, some verification is in order between a physical strain gauge and the virtual supposedly equivalent. However, the analysis in the digital twin applied here is for large component experiencing heavy external loads, and structural integrity is more a focal point than in drivetrain design, it still is a sufficient way to illustrate the digital twin premise. This shows that the approach is feasible, and combining this with a digital twin of a drivetrain, a complete system model of an offshore wind turbine would be available.

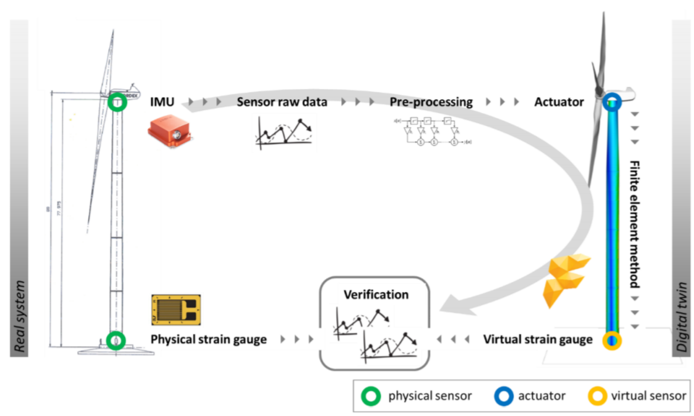

FIGURE 1: Digital Twin by Fedem Technology/SAP SE [23]

Larger companies than Fedem Technology has approached the digital twin scheme. For example, General Electric (GE) has conceptualized digital twins in general, and specifically for the wind energy sector. They empower it by an industrial industry platform named "Predix", to achieve the requires connectivity [24]. The industrial internet is meant to be comprising intelligent machines, advanced analytic and people at work. GE also considered the savings available in any industry if incorporating industrial internet combined with optimizing performance by using digital twins [25].

The wind energy industry is showing an unprecedented effort to developing digital twins. The motivation lies with the benefits a digital twin provides; predictive system behaviour, simulations of rough environments, less downtime, less man hours for maintenance and improved lifespan for their systems [26]. This all leads to a decrease in expenses. Offshore wind turbines are in areas that are harder to reach and has to be approached in a certain weather window [27]. Additionally, offshore wind turbine farms are growing larger, more expensive and further away from land so the incentive for a decentralized maintenance programme is there in a much larger aspect than for the onshore wind turbines [28].

SHIPPING - INDUSTRIAL CASE STUDY

This section is found by an industrial case study done by the author at Wilhelmsen Ship Management, with thanks to Ro-Ro vessel manager Jon Helge Ulstein [29]. Ulstein is responsible for the management, including technical on these vessels and has substantial experience in the shipping industry, both on the yard and on the operational side.

The maintenance schemes utilized in shipping today are largely planned maintenance schemes (PMS), with a few exceptions on the offshore supplier vessel side of the industry. PMS comprises a periodical maintenance, with frequencies based on maker's specifications and/or by running hours of a system. Generally, the step into condition monitoring (CM) has yet to be taken, in spite of the vast potential savings found in decreased off-hire and down time. The control systems onboard the vessels are used only to monitor and provide alerts for the day-to-day operation. However, collecting and harvesting these datasets is not done to onshore ship managers or other stakeholders. By advancing from PMS, CM is preferred, and in the shipping industry this would imply meeting the requirements for the CM class of vessels, set by the Class Societies (e.g. DNV-GL) [30]. Ulstein's vessels have this CM class and by offline collecting data from 84 sensors, comparing to a close-to-new baseline and outsourcing the data certification, a report with operational recommendations is generated quarterly. This meets the requirements of the CM class, and it reduce the off-hire of these vessels. Benefits from this CM is dynamically decreasing by time however, as sub-optimal operations are detected.

Stepping up from this offline CM to online CM would be cost heavy, as todays sensor connectivity is provided through cabled systems. The sensors in questions are also cost drivers. Large vessels, as the Ro-Ro ships, will comprise considerable cost to cover cabling of the whole vessel. A wireless infrastructure by implementing an IoT solution is therefore paramount.

If these challenges were to be met and the cost and connectivity of the sensors, a potential for digital twin is enabled. The main reasons for down time is main engine, including the drive train, and ramp dysfunction for the Ro-Ro vessels. Additionally, Ulstein refers to the main driver for these dysfunctions; excessive vibration at unacceptable frequencies, that drives resonance. The drivetrain is sensitive in that matter.

The motivation for implementing a digital twin is significant, as the schedules of the vessels tightens continuously and the port calls are shortening. Unexpected off-hire or service work is a large cost driver and implementing CM in first instant and digital twin further on, would make maintenance an enabler, instead of a segment that control the business operation. Furthermore, by implementing a digital twin it allows the vessel manager to get quicker overview of their vessels, by simple color coding and intuitive visualizations. This creates room for better time management. Hence, this opens up the possibility for a vessel manager to manage additional vessels, making the business increasingly efficient and allowing the vessel managers to spend their time on the most urgent matters. Moreover, spare parts are a capital cost when considering the traditional PMS system, a vessel needs to have spare parts available at all times, in case of unexpected failures. A digital twin, or even the simpler CM system, would diminish the need of this ”dead capital”. By being able to predict failure, it would then be possible to predict which port and what service personnel and spare parts are required. Accordingly it would then be possible to reduce crew number and to sail the ship at minimum crew. Ulstein refers to a simple example of a cruise vessel with high amounts of HVAC units, which each has a small engine; say you have a 1000 units, and use 1 hour for planned maintenance on these periodically - by predicting failure it is then possible to save 1000 man hours. Needless to say, this cost reduction is attractive for ship owners and managers.

Ulstein proposes a use of the ship yard's already existing model of all systems as the digital twin model, a physical based model as such. Both CM, predictive maintenance and behavior analysis could then be performed. The behavior analysis could be both based on changes in internal and external conditions. Exemplified; if the sea temperature changes with 3°C it could then be possible to map the sensitivity of the HVAC and cooling systems on the vessel. It is then possible to forecast operations. When connectivity and cost challenges are solved, Ulstein explains that there should be no other significant reasons to *not* implement a digital twin solution, and that the digital twin will be the future of ship operations, leading the way for autonomous vessels.

DIGITAL TWIN FOR CONDITION MONITORING OF DRIVETRAINS

A drivetrain is a complex multi-body system containing several rotating components. By a system-identification approach, an overall diagnosis of fault detection and data acquiring could be done [31]. To model a digital twin of the drivetrain properly, both the dynamic aspect, contact analysis and power transferring through gear teeth contact should be considered. Contact analysis can generally by done numerically by either finite element method (FEM) or by multi-body simulation (MBS) [32] [33]. Other approaches has been researched such as the study of Nejad et al. [34]. This method is a base for ultimate limit state (ULS) design, and does not include internal dynamics which would have to be accounted for independently.

FEM is suitable for high accuracy and detailed numerical modelling, whilst MBS is significantly less time consuming [32]. MBS contain rigid and flexible bodies that are connected with force elements [35]. The flexible bodies could be modelled in FEM and imported into a MBS program [36] [37]. However, this increase in detail level and additional information about internal dynamics makes the computation more complex and time consuming.

Condition Monitoring

Drivetrain failure, and specifically gearbox and bearing-failure, leads to more downtime than other components and are of high significance as fault detection goes in the offshore wind industry [38, 39]. This section will therefore describe the state-of-the-art drivetrain condition monitoring tools, focusing on vibration analysis. This type of analysis is of most significance regarding analyzing these most sensitive parts in a drivetrain [39].

Vibration Analysis For rotating machinery, vibration analysis is the most used monitoring strategy. This strategy is employed both at gearbox, rotor and blades, but also at bearings and tower [40]. The tower and the bearings absorbs energy supporting axial and radial forces, and will receive a certain vibration planted from e.g. the gearbox or the rotor. Gearbox failure often start at the bearing as they have high probability of fatigue damage [16]. For wind turbines the monitoring is performed by evaluating the vibration at the wheels and bearings of the gearbox and generator. Especially the main bearing is considered, as it significantly influences the health of the other bearings [41].

Depending on the component analyzed, different frequency ranges should be used. For low frequencies a position transducer is applied, medium frequencies employ velocity sensors and high frequencies require accelerometers [42]. When selecting a sensor it is important to evaluate both dynamic range and sensitivity of the sensor. This is especially important for low frequencies where the amplitude from acceleration can be small. In the interest of deciding sensor type, ISO 13373-1 provides typically used transducers [43]. Furthermore, ISO 10816-21 provides standardized measurements, assists in evaluation of them and makes it possible to compare evaluations the vibration measurements in wind turbines. For this evaluation, specific zones are laid up with corresponding boundary conditions, however acceptance values needs to be confirmed with the manufacturer [44]. To to evaluate the vibration severity one can compare to zone boundary layers. This comparison is done with the root mean square values of the mm/s velocities of the real time series data of the vibration, and the zones are found in ISO Standard ISO10816-1 and described as [45]:

Zone A: The vibration of newly commissioned machines normally falls within this zone
Zone B: Machines with vibration within this zone are normally considered acceptable for unrestricted long-term operation
Zone C: Machines with vibration within this zone are normally considered unsatisfactory for long-term continuous operation. Generally the machine may be operated for a limited period in this condition until a suitable opportunity arises for remedial action
Zone D: Vibration values within this zone are normally considered to be of sufficient severity to damage the machine

The table that shows the boundary ranges for vibration velocity is shown in Figure 2.

	Range of typical zone boundary values for non-rotating parts r.m.s. vibration velocity mm/s			
0,28				0,28
0,45				0,45
0,71				0,71
1,12				1,12
1,8	Zone boundary A/B 0,71 to 4,5			1,8
2,8				2,8
4,5		Zone boundary B/C 1,8 to 9,3		4,5
7,1				7,1
9,3			Zone boundary C/D 4,5 to 14,7	9,3
11,2				11,2
14,7				14,7
18				18
28				28
45				45

NOTE 1 This table only applies to machines for which specific International Standards have not been developed and for which there is no suitable experience available.

NOTE 2 Small machines (e.g. electric motors with power up to 15 kW) tend to lie at the lower end of the range and large machines (e.g. prime movers with flexible supports in the direction of measurement) tend to lie at the upper end of the range.

FIGURE 2: Range of typical values for zone boundaries [45]

Also, various bearings require a different specific number of sensors at different locations within the drivetrain. Frequency ranges relevant for wind turbines, and direction of measurement are procured in certification provided by DNV-GL [39]. These values shows what a data-based condition monitoring scheme will use as boundaries and benchmarks for operation. However, further interpretation of the data is needed to be able to improve operations.

Several distinctive ways of doing vibration analysis are analyzed in current literature on vibration analysis of drivetrains.

Liu et al. propose fault diagnosis based on local mean decomposition technology, applied to the gear mesh frequency signal [46]. Feng et al. consider a diagnosis method based on amplitude and frequency demodulation [47]. Miao et al. considers a zoom interpolated discrete Fourier transform, found from multiple modulations [48]. Jayaswal et al. shows different vibration analysis techniques on bearings, and sees that bearing fault is found at an earlier stage by using vibration analysis. By employing FFT and studying the spectrum bearing condition is accessed [49]. Abdussiam et al. discuss the use of Time Encoded Signal Processing and Recognition (TESPAR) in vibration analysis [50]. Dalvand et al. proposes an instantaneous frequency based method with envelope analysis of vibration signal [51].

Regarding fault detection- using vibration data and transforming it from the time domain to the frequency domain opens up possibilities to see patterns in output that could be used not only to predict faults. Not only at the selected spot, but whilst using a model based approach by digital twin, it is also possible to predict faults elsewhere in the system, as it is interconnected.

As discussed, there are mainly three approaches to analyze data generated from drivetrains; data-driven, data-modelled or physical-based. The data-driven approach has an benchmark of sub optimal performance and related alerts are then triggered. This approach is collecting data points and comparing it to standards, recommendations from manufacturer and from class societies.

The data model based approach is collecting data and considering correlations with certain faults. By utilizing this approach it is necessary to have a large amount of data and higher level of competence in data science. This approach is a machine learning approach and could also detect issues and fault driving parameters that outside the known research in the field.

A physical based model driven by data input, but utilizing the equation of motion to predict behavior, is a good aim of a digital twin and is possible to have benefits from even without large amounts of data sets available. This paper will focus on the physical based model driven by data input digital twin. It is more intense regarding domain knowledge and computational time, however this approach has a model with universal validity and the benefits from collecting sensor data from anywhere of the twin is then achieved [3].

WHAT STEPS TO MAKE

Considering the steps to make when building a digital twin there are a few common denominators that have to be implemented. Starting with the sensor data collecting, going forward to a model that comprises the actual digital twin and lastly you have an output of remaining useful life (RUL) and fault prediction. To achieve a sufficient data collection one needs to have the correct sensor technology in place to get what data needed at the frequency required. Additionally, knowing where to place your sensors is essential. An efficient placement of sensors is reliant on a sensitivity analysis performed [16].

When the data is collected a data quality analysis should be performed added with a sufficient connectivity. When looking at the offshore wind turbine industry and the shipping industry, the connectivity is definitely of a higher lever for the offshore wind turbines than the shipping vessels, as they are stationary versus the every changing position of a vessel. When the data is arriving at the model, the data has to be analyzed. This is where the different approaches are found; data-driven, data model approach and physical based model approach. Considering the physical model this is where the equation of motion (EOM) is put and this is where fault modelling algorithms are comprised. There are several challenges when doing so, some of which are discussed in this paper, but the advantages here have been mentioned earlier. Lastly, the output from the model has to be analyzed for RUL and fault prediction schemes. This approach is simplified in the figure below.

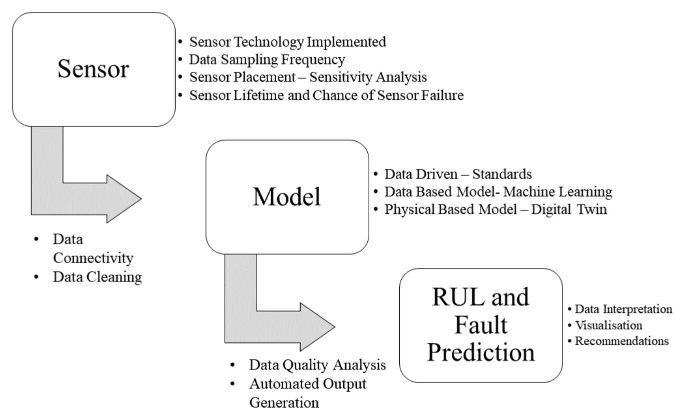

FIGURE 3: Digital Twin Methodology

RESULTS

For method verification reasons this paper will consider a simple drivetrain test rig in a lab environment, equipped with optical sensors for vibration analyses that detects displacements. The drivetrain is shown in Figure 4.

The sensors are placed to detect displacements in horizontal (X) and vertical (Y) direction. By utilizing this simple drivetrain instead of a gearbox, it is easier to detect flaws in the methodology approach. Further use of the method could then be employed and this method could be utilized for other and more intricate and complex models. Additionally, NTNU has a simple drivetrain available in real life for testing in lab. The

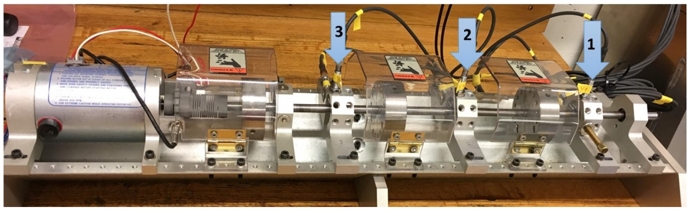

FIGURE 4: The drivetrain test rig at MD Lab, NTNU [52]

lab is the *Marine Drivetrain Research Lab* (MD Lab) at NTNU Department of Marine Technology [52]. This model is simplified and several modelling approaches of this simple drivetrain were tested. The modelled drivetrain is shown in Figure 5. More details and results from this test can be found in Johansen S. [53].

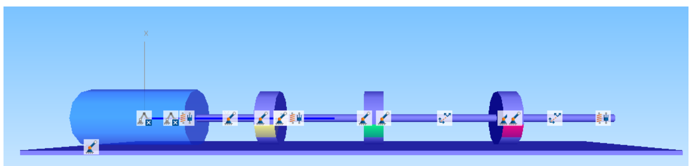

FIGURE 5: The drive train test rig modelled as a Digital Twin

For the modelled digital twin of the drivetrain test rig a few concluding remarks are evident. For the one degree of freedom (DOF) modelling approach the results are satisfying, whilst for the five DOF modelling approach the increased fidelity lead to less accurate simulations. Thus, the increased fidelity leads to decrease in accuracy in this case. For the five DOF models, the modelling approach that was utilizing a flexible shaft model, rather than a rigid shaft model, led to the least errors. The stiffness values for bearings that led to the best results were the ones from a tuning approach. It could be argued that coupled effects are a part of the reason for this result. More information on the related angular displacement is required. Still, the five DOF model with flexible shaft is close to measured values, especially in Y-direction. Errors in X-direction consequently for all models applied is argued to be related to an error in the modal analysis underestimation of stiffness, coupled effects or resonance, or a combination of these. Two of these results are shown in Figures 6 and 7. Fault modelling in the MBS can also be done with stiffness change in the bearings or by a force vector input in the bearings [54].

CONCLUSION

A digital twin is definitively relevant when considering assets that are of high value and that has a hard-to-access location. Then the benefits from a holistic health monitoring

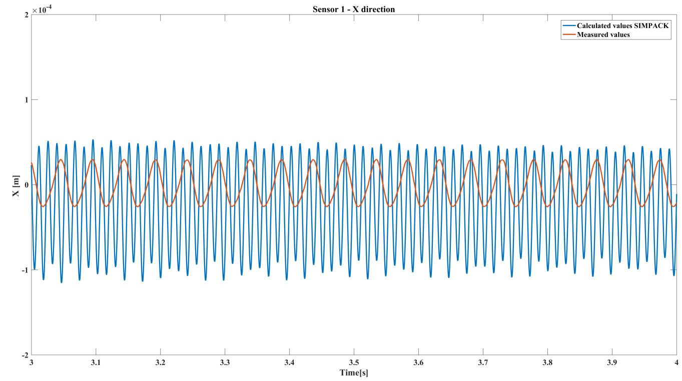

FIGURE 6: Test rig drivetrain modelled as 5 DOF with flexible shaft at sensor 1 in X-direction (horizontal)

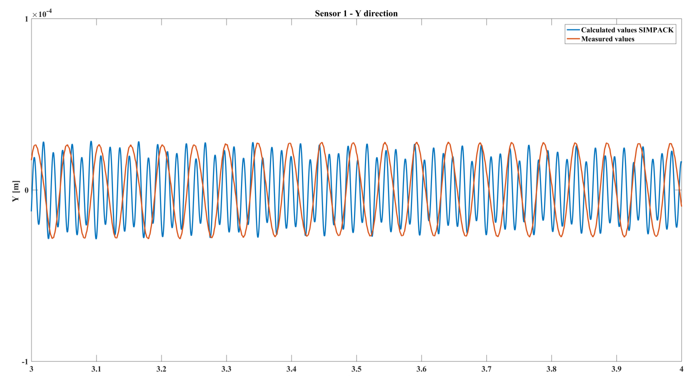

FIGURE 7: Test rig drivetrain modelled as 5 DOF with flexible shaft at sensor 1 in Y-direction (vertical)

will aid in decreasing maintenance costs and down time, saving asset owners capital. For offshore wind industry and the shipping industry both high value assets and hard-to-access locations are relevant. Increasing connectivity and IoT solutions over both fleets leads to a higher probability of implementation. Considering one of the largest contributor to down-time, the drivetrain, a physical based digital twin model was build, by different approaches. The results shows that higher fidelity had more inaccuracies, while the lower fidelity model was more accurate. However, a lower fidelity model does not meet the requirements for a digital twin. A data model driven digital twin would be harder to build, as this requires the use of Big Data which is not currently available. A data driven model is however often used, though it has a drawback that the digital twin could fill; the predictive and holistic health monitoring.

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