A Digital Twin of the Research Vessel Gunnerus for Life Cycle Service

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***Abstract*—Digitalization has become a key aspect of making the maritime industries more innovative, efficient and fit for future operations. One of the most attractive aspects is the concept of digital twins, which refers to a digital replica of physical assets, processes and systems that can be used as advanced tools for design, operation, and maintenance. This paper introduces the development of the digital twin of the research vessel Gunnerus in Norway, which will be a significant scientific and operational achievement for the maritime industry, making efficient and safe offshore operations possible. It enables data exchange safely and easily between different sub-systems, modules, and various applications. Thus, the twin ship can provide an integrated view of the ship's various physical and behavioral aspects in different stages, and allow simultaneous optimization of functional performance requirements. In addition, it enables advanced control and optimization, e.g., creating more reliable prediction for flexible objectives (time, output, emissions, fuel consumption), and executing day-ahead and long-term planning for operations. Several related applications are presented in the end to confirm the effectiveness of the digital twin ship system.**

***Index Terms*—Digital twin, system design and realization, co-simulation.**

I. Introduction

NORWEGIAN maritime industrial cluster is a world leader in developing complex, customized ships and offshore vessels to the global market, particularly for demanding operations, where safety and environment are focused areas [1]. Today's maritime engineering systems are operating in highly dynamic environments. The challenge is to develop a concept leveraging on the different levels of system specific services already provided by manufacturers, where safety and efficient performance of complex integrated systems can be managed from the early stages of a new vessel manufacturing project and throughout the vessel's life cycle. Advanced marine systems should be able to decide between different actions, adapt to dynamic environments and execute high-level task specifications without explicitly being programmed. To meet requirements, control system will need access to very realistic models of the current state of the process, and in addition, their own behavior in interaction with the real-world environment.

Modern marine vessels operate increasingly autonomously through strongly interacting subsystems [2]. Systems and sub-systems exchange data and make coordinated operational decisions, ideally without any user interaction. Designing, operating and life cycle service to support such vessels is a complex and intricated engineering task requiring an efficient development approach to consider the mutual interaction between subsystems and the inherent multi-disciplinarity. Scalable simulation technologies should take the lead in this process. Furthermore, the work flow in maritime industry does not stop after vessel delivery. Through system updating or due to life cycle maintenance, subsystems can be changed and updated. To make sure of that, product design and useability need to be coupled already during early stages of design, which requires traceability through a performance data management system that spans the entire vessel lifecycle.

The recent years have seen an increasing interest in developing and employing digital twins [3], big data [4] and cloud computing for maritime industrial system design, ship intelligence, and operational service. Increased use of advanced tools for designing and evaluating system performance, safety and structural integrity are generating a range of digital models of a vessel and its equipment.

This paper presents a digital twin of the research vessel Gunnerus. As illustrated in Fig. 1, it is a digital open marine industrial infrastructure not only for overall system design, allowing configuration of systems and verification of operational performance, but also more focusing on providing early warning, life cycle service support, and system behavior prediction. The maritime digital twin models should be constructed prior to or in parallel with the actual building of a vessel, enabling virtual manufacturing and commissioning, integration testing and analysis in the earlier stage. During the operational phase, the digital twin becomes a system for integration, processing and analysis of the operational data. Ideally, the digital twin will provide decision support and predictions for a ship owner, subsystem manufacturers and safety training/improvement for crew and operators. It will enable the use of model-based/data-based simulation in combination with sensor measurements from the real vessel, without the need for physical inspections. The digital twin tracks information on all parameters to define how each individual module and sub modules behaves over its entire useful life, including the initial design and further refinement, manufacturing related deviations, modifications, uncertainties, updates as well as sensor data from on-board systems, maintenance history and all available historical and fleet data obtained using data mining. All research outcomes will be further used for ships that are either autonomous or remote-controlled for safety and reliability enhancement [5].

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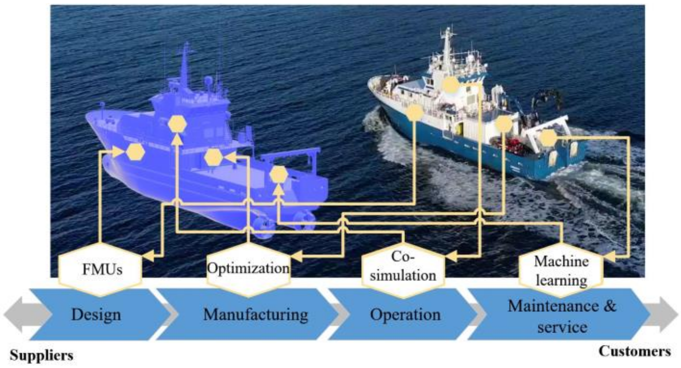

Fig. 1. Digital twin of Gunnerus ship.

Using digital twins for marine engineering could bring the following advantages.

1. ***Reduce development time and enhance production efficiency:*** provide an integrated view on the vessel's various physical and behavioral aspects in all stages, allow optimization of all functional performance requirements throughout the entire development cycle.

2. ***Improve operational flexibility and reduce cost:*** create more predictable, faster starts for flexible objectives, execute day-ahead and long-term planning for improved operations, reuse the sub system models, data and operational sources.

3. ***Enhance the life cycle value chain and improve the system performance and health conditions:*** allow data exchange between different sub-systems, modules, and proprietary applications; make remote access systems assure system availability via digital twins, and early warnings utilized for short time technical support.

4. ***Improve quality and efficiency of maritime product and operation approval and certification processes:*** combine simulation models and sensor data on an open platform; facilitate the design and verification of cyber-physical systems.

II. RELATED WORK

The digital agenda is one of the pillars of the Europe's growth strategy. It lists ship intelligence as one of the main areas through which to achieve growth. In marine system and transport, digitalization can significantly improve design, operation and management through accurate information on operational and infrastructure conditions and on the location of vehicles and/or system behavior models. Better access to and sharing of digital data (traffic, travel, vehicle, cargo etc.) for both public and private stakeholders along the supply chain can foster seamless information flows, and open up a wide range of new business opportunities.

The last few years have witnessed a strong, renewed interest in digital twin technologies. Their applications include manufacturing, agriculture, energy management, automotive industry [3]. Digital twins integrate artificial intelligence, machine learning and data analytics with data to create living digital models that update and change as their physical counterparts' change. A digital twin is a model of a physical asset, implemented for example as a mathematical model, an information model or a visual model. Machine learning offers a way to create and update models of the physical system based on sampled data [6]. In various industrial sectors, digital twins are being used to optimize the operation and maintenance of physical assets, systems and manufacturing processes. It is a formative technology for the Industrial Internet of Things (IIoT), where physical objects can live and interact with other machines and people virtually. A digital twin can be used for monitoring, diagnostics and prognostics to optimize asset performance and utilization. Therefore, complex prognostics and intelligent maintenance system can leverage the use of digital twins in finding the root cause of issues and improve system productivity.

The main difference between digital twins and generic models is that the former are specific to, and reflect their physical counterparts, with dynamic data flow interaction. Normally, modelling and simulation is used to build a system and sub systems in a single alone software environment for design, control and optimization. When the complexity of the whole system increasing to a certain level, such as a surface vessel with multi-domain components, modelling everything in one software is almost impossible. The digital twin follows its corresponding real life twin through its life cycle, through collecting sensor measurements, simulation model updates and software upgrades.

Models are key issues in a digital twin. The last decades have seen an increasing interest in developing computer-based design and analysis tools for different applications including marine industry. First, some general-purpose simulation environments are well-known in research and education, including MATLAB/Simulink [7], Modelica [8], etc. In parallel, a great number of specialized analysis software for structures, hydrodynamics, computational fluid dynamics, power systems and control systems are currently used in the design process to assess special sub-system performance. Integrating the above two approaches in maritime design processes is non-trivial due to differences in the emphasis on system modularity and model accuracy in the software.

The next key issue is data sharing and models integration. Functional Mockup Interface (FMI) [9] offers model exchange and co-simulation mechanism to couple different models. The essential difference is that units compliant with FMI for model exchange expect to be solved by a given master algorithm, while those for co-simulation, on the other hand, contain a solver so that the master algorithm is only required for coordination of data exchange. A co-simulation mechanism provides a solution to how to specify the parameters and variables to exchange and how to make it happen.

In essence for maritime industry, the digital twin should be able to take advantage of all digital information available for an asset: system and data information model, 3D visualization models, mathematical models, dependability models, condition and performance indicators and data analytics. An increasing number of systems and processes onboard of a modern vessel, are dependent on computers and networks for monitoring and control. Feedback loops from system measurements are included in the computations and affect the controllers.

More importantly in current maritime industry, a balance between the number of defined domain models and the scale of the whole system will be met to make the digital twin system flexible and fast enough. Maritime systems communicate through a number of formats and protocols. The variety in protocols and in installed instruments and systems makes it difficult integrate with new systems, especially with those which require information from many different subsystems. In addition, each of these protocols must be set up with explicit knowledge of where and how to access each piece of information. Open source is a key factor to establish a cloud enabled co-simulation platform and model eco-system for collaborative & managed model sharing and time-domain system simulation. The core components should be open source and governance by the research consortium. The sub models, apps, tools, service will be offered in the digital twins at various IP terms. In this way, the industrial partners could get first-hand help and speed up the design, operation.

As mentioned above, digital twins are promising, but challenging in maritime domain. From next section, we will introduce how to build our digital twin of the research vessel (RV) Gunnerus.

III. Maritime Digital Twin Ship

The RV Gunnerus [10] from NTNU is used as a testing platform for our research, as shown in Fig. 1. It is equipped with the latest technology for a variety of research activities within biology, technology, geology, archaeology, oceanography, and fisheries research. Main dimensions of the vessel are given in Table. I.

The digital ship can be either deployed on its physical counterpart, or placed onshore in a remote control center given the sensor data is able to be transmitted via gateway. A historical dataset can be generated by taking all-year measurements from the onboard sensors placed on the physical ship, e.g., the ship hull, the engine and the thruster. Digital models of systems and sub-systems in simulation can thus be refined using combined model-driven and data-driven approaches [11] to ensure the fidelity of the digital twin of a ship. Based on the digital ship simulation, a variant of control levels, from remote control to fully autonomy can be implemented in the digital-twin system. As a result, different onboard support tools, such as visualization, task configuration and high-level applications like path planning can be included in the system. The result of the onboard support tools will either be fed into simulation for validating operations or be treated as metrics for decision making on the physical ship.

TABLE I
MAIN DIMENSIONS OF GUNNERUS SHIP

Parameter	Value
Length overall (Loa)	36.25 m
Length between pp (Lpp)	33.90m
Waterline length (Lwl)	29.90m
Breadth middle (Bm)	9.90m
Breadth extreme (B)	9.90m
Depth mld. Main deck (Dm)	4.20m
Draught. Mld (dm)	2.70m
Deadweight	165t

Although the implementation of the digital twin has some current limitations, such as insufficient possibilities for synchronization between the physical and the digital world, the lack of high-fidelity models for simulation [5] [12], as well as the challenges for gathering and processing large data sets, Fig. 1 shows a sound conceptual framework, from which a digital ship can be refined via historical/ onboard sensor data using data-driven methods and be combined with other models used in marine operations for onboard support or advanced control. As a sequence of evolution from simulation, virtual prototyping to digital twin implementation, a twin ship with high fidelity can thus be realized and used as digital tools for either decision making in remote control center, or control basis for autonomous ship.

Four key issues in Gunnerus digital twin will be introduced separately, including:

- Co-simulation mechanism as digital twins platform;
- Data collection and transmission;
- Models and sub-domain models for co-simulation;
- Enabling tools for onboard support on the ship or onshore.

A. *Co-simulation Mechanism as Digital Twins Platform*

Co-simulation is a promising technology that enables different sub-systems to be modeled and simulated in a distributed manner [12]. In general, it is difficult to apply models implemented in different tools and domains into one simulation. However, with the emergence of two noteworthy standards, namely the High Level Architecture (HLA) and the FMI, different sub-systems can be modeled separately and composed into a global simulation where each model is being executed independently, sharing information only at discrete time points. In this work, only the FMI is considered. However, in order to effectively make use of and connect different sub-systems, some higher form of orchestration layer is required. Several such orchestrators exist, both open-source and commercial, each with its pros and cons. An overview of various open-source solutions is provided in [12].

We rely on the open simulation platform (OSP) [13], which is specifically designed for maritime industry for performing co-simulation and sharing simulation models, e.g., the Functional Mockup Units (FMU). The OSP architecture is shown in Fig. 2. Thus, a ship can be implemented as an aggregation of several independent sub-models including the hull, thrusters, and power system, etc.

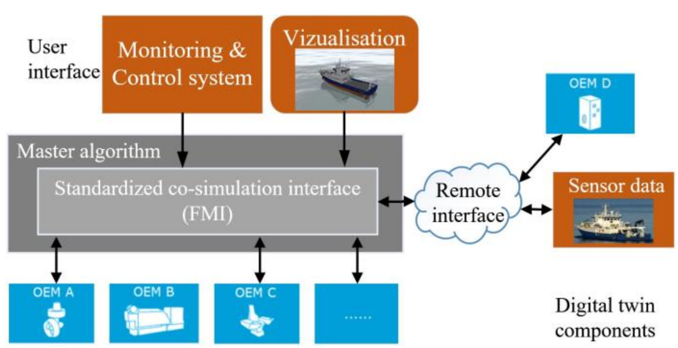

Fig. 2. Open simulation platform.

The OSP consists of a co-simulation library written in C++ with additional interfaces for C and Java. A simple web GUI and command line interface (CLI) is also available. The OSP has developed the OSP-IS, an addition to the FMI that provides a method for adding semantic meaning to model interface variables. Additionally, proxy-fmu [9] will be used to enable co-simulation of otherwise incompatible simulation models and the System Structure and Parameterization (SSP) standard will be used to facilitate the configuration of the overall co-simulation structure including its parameterization and connections. To simplify the process of creating SSP compliant systems, the project partners have developed SSPgen, which allows such systems to be defined using a domain specific language that also enables the OSP-IS to be applied in a SSP context. Currently, OSP is valid for the public. The detailed information could be found in [13].

B. Data Collection and Transmission

With the growth of emerging demands from marine applications, such as seabed survey, pipeline maintenance, and wind turbine installations, the main concern for the maritime industry and shipowners is how to achieve efficient marine operations while ensuring safety. Today's maritime engineering systems are often equipped with various sensors and operating in highly dynamic environments. Incorporating sensor data not only about the internal status of machinery, propulsion, and engine systems but also from a camera, lidar, radar, sonar, and GPS/INS sensors improves the situational awareness of the ship. Fig.3 depicts the scope of the research, illustrating how to use historical/ live data and co-simulation technology to achieve a digital-twin system. All these data sources, including the status from ship, crane and engine, can be transferred via a 4G connection to an onshore control center to conduct operational planning. A NUC PC is deployed on Gunnerus, from where the Message Queuing Telemetry Transport (MQTT) network protocol is used to publish data messages from different data sources on demand. Then, a local server is used to subscribe to each data source to store it in a database. Finally, the data is applied and analyzed on the digital twin and transferred back to Gunnerus to enhance operational planning and decision-making.

C. Models and Sub-domain Models for Co-simulation

Models and sub-models that represent the physical systems and behavior are the building blocks of a functional digital twin. These digital representations of real systems and behavior can be physics-based, data-based, algorithms, or only graphics for visualization purpose.

The co-simulation approach for complex systems like a ship has its advantages in terms of modularity, modeling flexibility, and simulation efficiency. However, it always depends on the application to determine the complexity of the models to ensure both adequate simulation accuracy and efficiency. For example, as shown in Fig. 1, in the ship design phase, relative low fidelity models will be enough for fast prototyping to make a quick whole ship concept testing. After that, we need high fidelity model for detailed design, control and prediction. For the training phase, real-time models will be required. The balance between model complexity and efficiency has to be considered.

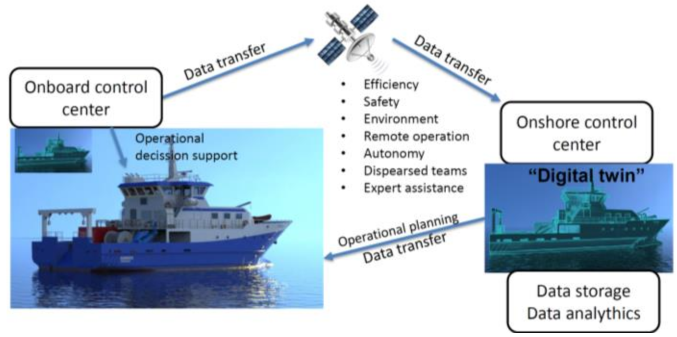

Fig. 3. Data collection, transmission and storage.

As mentioned above, the co-simulation framework allows for individual step sizes for each sub-simulator and orchestrates a network of multiple simulators using a fixed or variable step size to enhance the computation speed. It also often comes with a price of comprised accuracy. Another important aspect to the component models is the standardization of their interfaces. In many applications there is a need to design, simulate and execute a network of components from different users. In this regard, the SSP is an extension of the FMI standard to define complete systems consisting of one or more FMUs including their models with parameterization and solvers that can be transferred between simulation tools. The standard and specification enable faster construction of co-simulation simulators by simplifying the model connection process.

Table II includes a collection of components that represent the Gunnerus digital twin. They are developed by many different project partners with various methods and tools. Most of these components are open-sourced and support the FMI standard, except for that a license is needed for the Sintef© models. These components are used as reference models for the Gunnerus digital twin in the use cases presented in section IV.

It is worth to address that strong-coupled systems are not naturally easy to be handled separately in a co-simulation. As an example, the dynamical inertial impacts between the ship hull and the deck crane with a heavy payload cannot be neglected during operation [14]. In this very specific example, the payload and the crane can be connected via a flexible cable and treated as one component. The connection between the ship hull and the crane base can also be represented by a spring-damper system with extreme high stiffness and low damping coefficient. However, it requires extreme high computing resource for real-time simulation which is critical for crane operations in this application. Alternatively, the forces from the crane, including the payload, can also be approximated as external forces applied to variant attacking points on the ship hull during operation.

Table II Reference models for the Gunnerus twinship (all details could be also download from OSP webpage [13])

Subsystem	Component	Tool/code	Providers
Vessel	Hull	Vesim®	Sintef©
	Thrusters, include PMAzimuth thrusters and bow thruster	Vesim®	Sintef© Kongsberg©
	Power plant	20-sim®	Sintef©

	Thruster drive	20-sim®	Sintef©
Deck machinery	A-frame (+controller)	20-sim® Simulink	NTNU©
	Palfinger© Crane (+controller)	20-sim®	NTNU©
	Winch (+controller)	20-sim® SimulationX	NTNU©
Environment	Wind	Simulink®	Kongsberg©
	Current	Simulink®	Kongsberg©
	GNSS sensor	C++	Kongsberg©
	VRU sensor	C++	Kongsberg©
	Gyro sensor	C++	Kongsberg©
Controllers	DP controller	Java	NTNU© Kongsberg©
	Waypoint provider 2D/3D (reference target points)	Java	NTNU©
	Observer (position feedback)	Java	NTNU©
	Trajectory controller	Java	NTNU©

D. *Enabling Tools for Onboard Support*

Fig. 4 illustrates a scheme of enabling tools for onboard support in our digital twin system. First, the digital twin can store millions of data points from the physical vessel for different types of operations. A meaningful usage is model based sensitivity analysis - to model the relevant data and compute how much the model inputs contribute to its output. Developing such a supporting tool makes sense, for example, for energy consumption, one can analyze what the main factor is during the operation and take alternative solutions to save the consumption. Note that the data sensitivity analysis module is the basis of the scheme. It takes the ship status, the operational commands and the environmental data as input and the designated metric, e.g., ship position, as output, to quantify how much the input contributes to the output. The result can benefit both the optimizing and the prediction phase.

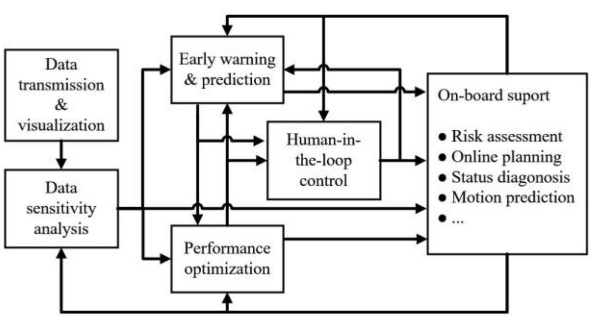

Fig. 4. Digital twins for maritime prediction and maintenance.

Second, the digital twin plays the role in modelling and simulation in the virtual world before executing any onsite operations, for a comprehensive understanding of certain specific operations such as mooring, dynamic positioning and crane lifting. Dynamic optimization refers to the state of the ship and the mission being executed. It considers constraints and generates optimized references for control; meanwhile it formulates the references as prior knowledge for prediction of future operation, as far as the control couples with the optimization module. Similar couplings exist between the prediction module and the control module, as they are in essence a complete closed-loop system. In this part, focuses are placed on the creation of valid models by either applying mathematical models or using data-driven approaches in marine operations. An example is the parameter identification of ship model. Another modeling example is to create a ship motion predictor. The solution could be a hybrid modelling method that combines a mathematical model with a data-driven model to estimation ship position and heading in time series.

The "performance optimization" module plays a role in optimizing the instantaneous and transient control of the ship for efficiency or performance, making informed decisions regarding performance versus time, cost, physical constraints and maritime regulations. Path planning is one of the cases that the module will focus on [7]. The limited working space, the positioning, and the heading requirements for operations and the marine traffic nearby constitute a complex spatial environment. How to achieve efficient maneuvering in such an environment by taking certain optimal metrics like minimal time or energy is worth studying. Furthermore, the maneuver should also comply with maneuvering regulations such COLREGs, so as to make it more applicable in real situations.

Taking the results from above modules, the "human-in-the-loop/automatic control" part will focus on either assisting operators or taking the operation in an automatic manner. For example, in order to assist the training of operators in simulator, a focus attention model can be established through expert knowledge and training data in simulator. Besides, auto-docking is an example for automatic control. The controller makes use of current sensor data to produce control commands to thrusters, thus realizing docking operation. The module is close to high-level application and therefore needs to take the specific requirements from the application into account.

As a result, the information from all different modules will be gathered together to establish an onboard supporting center, forming various tools ranging from risk assessment, maneuvering evaluation, sensor diagnosis to real-time planning. Note that, the onboard supporting tools can feed back to each module, to force it update. If a predictive path shows a potential failure of path following by the auto-control due to environmental condition change, a feedback to the optimization module will enforce it to re-plan.

To sum up, by effectively combining these modules mentioned above, it is possible to develop efficient onboard support tools for either assisting the operator during marine operation, or achieving automatic control of the operation.

IV. GUNNERUS TWINSHIP VALIDATION

In order to show how Gunnerus digital twin works, several related applications are presented as validation cases. All demos could be found on the following webpage (https://org.ntnu.no/intelligentsystemslab/gunnerus/digitaltwin.html).

A. *Harbor Docking*

Here, we take harbor docking operation as the first example to illustrate the possible solutions using the digital twin system, as shown in Fig. 5. In recent years, maritime industry including Kongsberg, Wärtsilä and DNV has put effort on implementing auto-docking systems [15]. The challenges for this application lie in the uncertainties from ship model and environmental effects, and the nonlinear control.

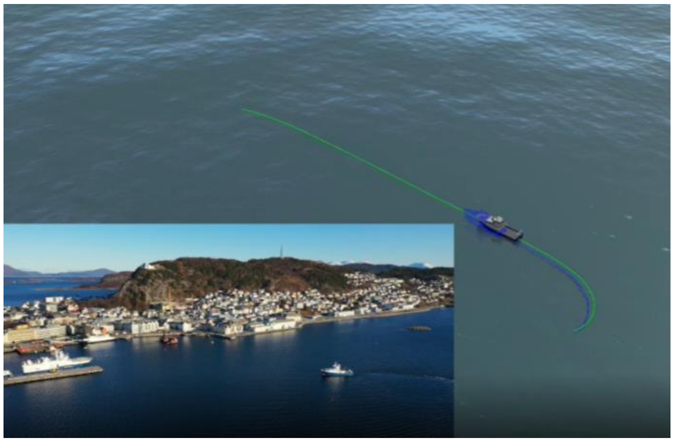

Fig. 5. Docking testing at Aalesund harbor in Norway. The grey ship and green trajectory present the real physical ship behavior; the blue ship and blue trajectory present the digital twin behavior; the video window shows the real operation as same as grey ship presented.

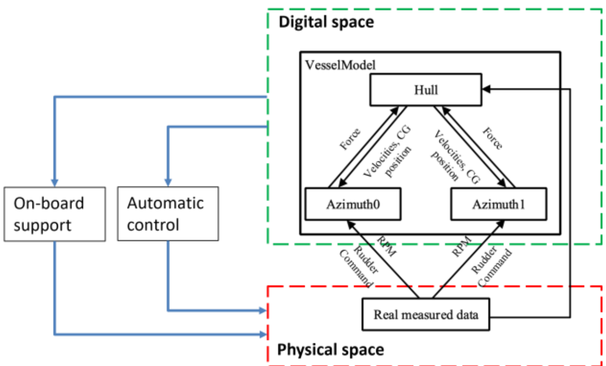

Fig. 6. Digital twin ship assists auto-docking based on co-simulation.

Given the historical operation data and ship motion data, the OSP framework introduced in Fig. 2 can be applied to simulate ship dynamics. As far as the fidelity of the model is acceptable, we can build up docking scenarios in simulator and invite shipmasters to perform the operation under different levels of sea conditions. The simulated data could then be fed into the tools to train the controller for ship docking, and the predictor for online estimating ship motion. This process will be run in a short period of time if there is enough simulated data for training. Further validation can be achieved and compared between the docking operation in field and in digital twin simulation. If validated, the twin ship in simulator can work in two modes. The first mode is to provide onboard support for predicting ship motion. By feeding the field operation data and ship motion data, the predictive ship motion can be feedback to the shipmaster during operation. The other mode is automatic control, which only takes filed ship motion data as input and produce operation commands for ship docking. In Fig. 6, each block in "digital space" represents an FMU with the signal communication specified. The involved components are provided by different stakeholders, as listed in Table II.

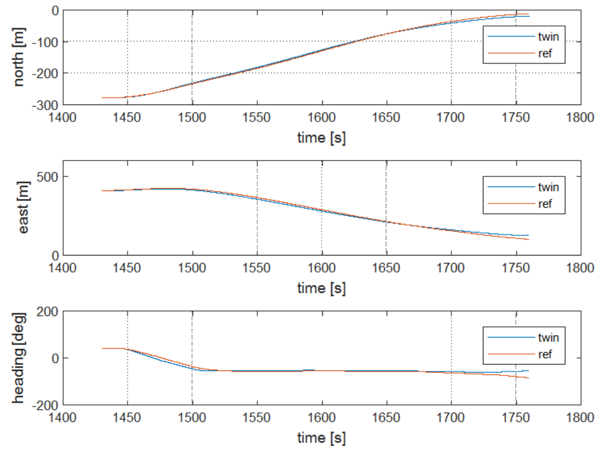

Fig. 7. Validation of twin ship docking in simulator VS real ship in field in terms of positions.

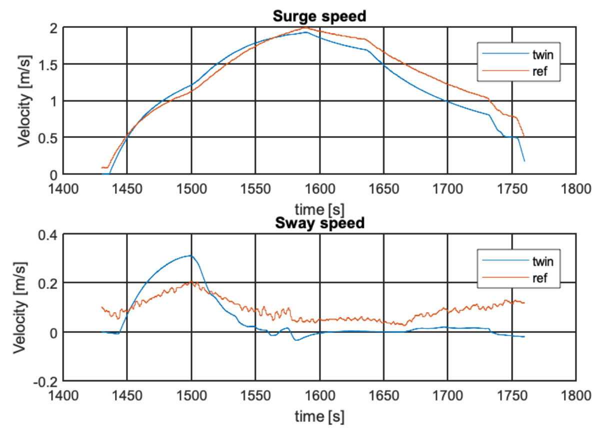

Fig. 8. Validation of twin ship docking in simulator VS real ship in field in terms of speeds.

A full-scale ship docking experiment is conducted in Aalesund harbour, Norway. When the ship Gunnerus is operated to dock to a berth, the implementation of twin ship docking in simulator is going on simultaneously. By feeding it the in-field ship operation and environment sensor data, the twin ship produces highly resemble trajectories and speeds as shown in Fig. 7 and Fig. 8. While the twin ship is not a complete duplicate of the physical ship, we are seeking to make them as indistinguishable as possible. Slight mismatches are observed, especially in speeds, as shown in Fig. 8. They might be caused by simulator fidelity which is somewhat deteriorated by the unmodeled uncertainties. Otherwise, the discrepancies may be resulted by the instrument errors, for instance, the wave and current measurements are usually difficult to accurately obtain. These unpredictable factors are unavoidable so far. Solutions to improve simulation fidelity will be further explored, e.g., to limit these factors to an acceptable range by trying best to improve simulation fidelity and preprocessing real world measurements. Overall, the validation supports the twin ship fidelity and approves predictive and control applications.

B. *PHM System*

Data-driven Prognostics and Health Management (PHM) [16] is an emerging engineering discipline that facilitates predictive maintenance scheduling. PHM system is expected to go far beyond today's best practice of preventive maintenance in the maritime industry, which uses predetermined maintenance intervals based on experience. The development of the twinship provides a unified solution to save different types of data of critical machinery in a database. These data can be then explored and utilized to establish a data-driven PHM system using data mining and machine learning (ML) algorithm [17].

Fig. 9 presents a schematic illustration on developing a data-driven PHM system for the diesel engine onboard Gunnerus. Engine data includes time-series data from installed sensors, event data registered by ship operators, and essential documentation provided by manufacturers. These data can be used by an auto-labeling pipeline to generate labeled data for ML model training. For instance, the time series sensor data can be aligned with the event data to identify normal operating data, fault data, and run-to-failure data. The normal operating data is used to train an anomaly detection algorithm, which can be used to tell whether the engine has deviated from normal operating conditions. A fault classifier is trained using the fault data, which classifies what kind of fault occurs on the engine. The run-to-failure data is used to train an ML regression model that predicts the remaining useful life of an engine before it fails completely. These three different types of trained ML models can therefore provide essential information on the operating conditions, fault types, and remaining useful life of the engine through real-time sensor data. Such information will be used to inform the ship operators to develop an optimal maintenance schedule to the engine that eliminates failures, which is expected to be more effective and less costly than preventive maintenance currently used onboard.

Currently only anomaly detection and remaining useful life prediction models are developed for the diesel engine onboard Gunnerus. For anomaly detection, a long short-term memory (LSTM)-based variational autoencoder (VAE) is trained with normal operating data [18]. The computational cost of ML models is different in the training and deployment phase. In this case, the model is expected to be updated monthly so training costs would not be a problem. Training such a model takes about half an hour with one GTX 2080 GPU. The model consists of an encoder $p_\theta(z|x)$ and a decoder $p_\varphi(x|z)$ which is parametrized by an LSTM network of parameters, θ and φ, respectively. The LTSM-based VAE is trained to minimize the following loss function:

$$l = \sum_{t=1}^{T} -E_{z\sim q_\theta(z_t|x_t)}\left[\log p_\varphi(x_t|z_t)\right] + D_{KL}(q_\theta(z_t|x_t)||p(z)) \quad (1)$$

where the first term in the loss function is the expected negative log-likelihood, which can be replaced by the mean square error between the inputs x and reconstructed inputs $\hat{x}$. The second term is the Kullback-Leibler divergence between the encoder's distribution $q_\theta(z_t|x_t)$ and $p(z)$. The prior distribution $p(z)$ is specified as a multivariate standard normal distribution. The loss of a sequence of time length T is minimized. After the model is trained, the reconstruction probability $p(x|\mu,\sigma)$ is used as anomaly score, where μ and σ are the mean and variance of reconstructed $\hat{x}$. A deviation is detected as shown in Fig. 10. It was later confirmed by the mechanical engineer that it was an air filter clogging fault.

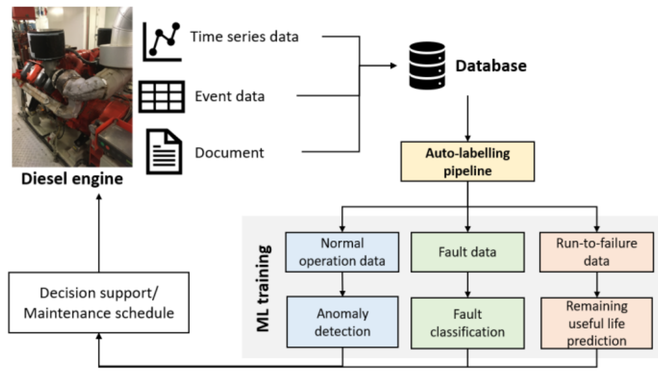

Fig. 9. Data-driven PHM system for diesel engine onboard Gunnerus.

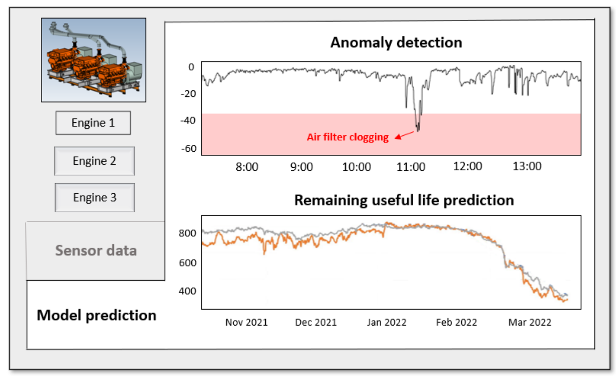

Fig. 10. Anomaly detection and fault prognostics based on ML. There are three engines on the ship. Two in operation, one as a backup.

For remaining useful life prediction, a LSTM network [19] is used. For each element in the input sequence, the LSTM computes the following function:

$$\begin{aligned} i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\ f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f) \\ o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) \\ g_t &= \tanh(W_g x_t + U_g h_{t-1} + b_g) \\ c_t &= f_t \circ c_{t-1} + i_t \circ g_t \\ h_t &= o_t \circ \tanh c_t \end{aligned} \quad (2)$$

where h_t and c_t are the hidden state and cell state at time t, x_t is the input at time t, h_{t-1} and c_{t-1} is the hidden state and cell state at time $t-1$, respectively. i_t, f_t, g_t, o_t are the input, forget, cell and output gates, respectively. σ is the sigmoid function, where $\sigma(x) = 1/(1+e^{-x})$. $\circ$ is the Hadamard product. W, U are the weights and b is the bias in the LSTM cell. Run-to-failure targets are constructed by the piece-wise linear degradation model. The model is trained with mean square loss. The model provides how much time an engine has left before it fails completely, and from validation in the lab, it predicts remaining useful life with high accuracy. The information in Fig. 10 can be provided to the vessel operator to schedule maintenance before completely failures.

C. *Demanding Pre-operation*

Offshore vessels often perform in harsh environments with wind, waves, current, and low temperatures. These operations need to be carefully planned and trained before execution. For this purpose, digital twin of the whole ship could be used as a valuable tool for pre-operation [20]. Digital twin not only allows iterative design of operational procedures by identifying inconsistencies and blunders, exploring “what if” scenarios during onshore planning sessions based on historical Metocean records and raising awareness on critical phases, but also it can be used in “toolbox-talks” just before the execution of the operation to rehearse the procedure based on the current ship loading conditions and nowcast of Metocean conditions.

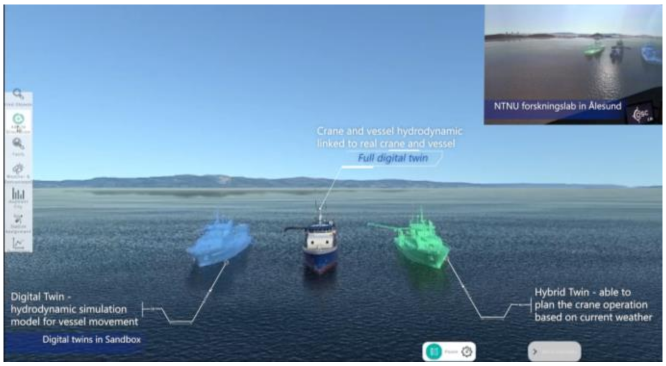

Fig. 11. Three real-time digital twins.

Fig. 11 illustrates the possibilities by presenting a snapshot of a remote monitored crane operation in a fjord. The operation lasted about half an hour. The data from the ship and shipboard crane was received in real-time via a 4G connection as detailed in Fig. 3. Fig. 12 depicts the corresponding four channels of crane data for the whole operation, based on which the crane status can be evaluated and used in the twin system. The three digital twins in Fig. 11 are all real-time representation of the same system consisting of the ship and crane subsystems. The blue system on the left is mirroring the real crane, but the movement of its hull is determined by harsher weather controlled in the simulation. The ship and crane in the middle are the exact presentation of the real system in real time operation. The hull of the green ship follows the movement of the real ship, but its crane is controlled by an operator in the remote centre to test alternative path trajectory in lifting operation. In this way, it allows the direct testing of “what-if” scenarios based on real-time current state of remote systems. All functions have been integrated into NTNU forskingslab in Aalesund based on the cooperation and support with Offshore Simulation Centre. A real-time online digital twin will enhance the operation safety and security in the following aspects:

- Explore the limits of procedural safety by simulating the operation in more extreme weather conditions, with identical current crane loads, deck arrangement, and ship ballasting;
- Find a proper way or alternative safer ways of performing the operation under certain harsh weather conditions.

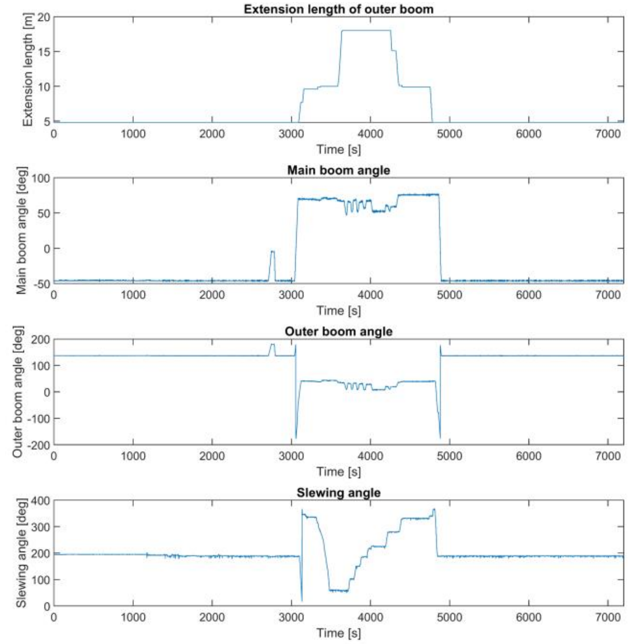

Fig. 12. Four channels of sensor data for crane status monitoring.

V. Discussion

In order to build a digital twin ship, we propose an architecture and concept using an open model and simulator platform. The Gunnerus digital twin as a prototype combines expertise from complementary disciplines including sensor technology, artificial intelligence, computer science, and maritime industry.

Many challenges arise when trying to fully represent the physical counterpart by the twin system in stochastic environment. One of the challenges is the high-fidelity models. As learned from the Gunnerus twin ship, the amount and quality of data is fundamental to establish the models for the twin system, e.g., either for identification of system parameters, or for development of ML models. Therefore, it is necessary to establish mechanisms to update models especially for these ML models regularly. Thus, the computational cost of ML models, such as the training time for the model in Section IV.B, can be relatively low, and the model is able to adapt to operation/environmental changes. Another challenge lies in co-simulation for digital twin implementation. For example, scalability shall be considered when it comes to industrial use of digital twin; insufficient synchronization and tight coupling issues may arise if the system becomes too complex and requires high computational effort; domain-specific challenge in FMU implementation also needs to be talked with.

The Gunnerus twin ship is our best try of digital twin systems for marine operation. Even though there is still room for improvement in terms of accuracy and efficiency, we believe the implementation will enlighten both maritime industry and academia in developing twin ships in near future.

VI. Conclusion

This paper has illustrated a digital twin of Gunnerus ship. All related key technologies including co-simulation, how to model components, data transferring, enabling tools utilization, are presented in details. The team at the Norwegian University of Science and Technology with our cooperated stakeholders will continue the work towards realizing a full functional digital twin of the Gunnerus, gradually improving its accuracy. Continued development of use-cases will provide meaningful on-board decision support for the crews of the Gunnerus. The other application is digital commissioning. If we can feed different kinds of industrial data into a simulator to create a digital-twin system, and use the simulator to verify the concept, the process and the control efficiency, it will definitely reduce development time and enhance production efficiency. On the other hand, from a methodology point of view, academic research can make use of simulated data to verify the effectiveness of the digital-twin system. Once there are enough real data available, the digital-twin system can be updated and serve as a digital replica of the physical system. As a result, both industry and academia could take advantage of the digital-twin system to realize high-level applications.

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REFERENCES

[1] DNV GL, 'Digital Twins at Work in Maritime and Energy', 2017. https://www.dnv.com/Images/DNV%20GL%20Feature%20%2303%20ORIG2b_tcm8-85106.pdf (accessed 11 July, 2022).
[2] B. V. Lierde, W. Cardoen, D. Radosavljevic, "Predictive Engineering Analytics for Shipbuilding - An Overview, Siemens PLM Software", 16th International Conference on Computer and IT Applications in the Maritime Industries, Cardiff, 15-17 May 2017, Hamburg, TUHH, 2017, pp. 351-400.
[3] H. Feng, C. Gomes, C. Thule, K. Lausdahl, A. Iosifidis, P. G. Larsen, "Introduction to Digital Twin Engineering", 2021 Annual Modeling and Simulation Conference (ANNSIM), pp.1-12.
[4] M. Hilbert, "Big Data for Development: From Information- to Knowledge Societies" (January 15, 2013). Available at SSRN: https://ssrn.com/abstract=2205145
[5] R. Skulstad, G. Li, T. I. Fossen, B. Vik, H. Zhang, "Dead reckoning of dynamically positioned ships: using an efficient recurrent neural network", IEEE Robotics & Automation Magazine, vol. 26, no. 3, pp. 39-51, DOI: 10.1109/MRA.2019.2918125, 2019.
[6] N. Jones, "Computer science: The learning machines," Nature, vol. 505, no. 7482, pp. 146–148, Jan. 2014.
[7] M. Safeea and P. Neto, "KUKA Sunrise Toolbox: Interfacing Collaborative Robots With MATLAB," in IEEE Robotics & Automation Magazine, vol. 26, no. 1, pp. 91-96, March 2019, doi: 10.1109/MRA.2018.2877776.
[8] A. Guironnet, M. Saugier, S. Petitrenaud, F. Xavier and P. Panciatici, "Towards an Open-Source Solution using Modelica for Time-Domain Simulation of Power Systems", 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2018, pp. 1-6, doi: 10.1109/ISGTEurope.2018.8571872.
[9] P. Fritzson, A. Pop, K. Abdelhak, etc., "The Open Modelica Integrated Environment for Modeling, Simulation, and Model-Based Development", Modeling, Identication and Control, Vol. 41, No. 4, 2020, pp. 241-285, ISSN 1890-1328.
[10] https://www.ntnu.edu/oceans/gunnerus (Date accessed 5-April-2022)
[11] R. Skulstad, G. Li, T. I. Fossen, B. Vik, H. Zhang, "A hybrid approach to motion prediction for ship docking- integration of a neural network model into the ship dynamic model, *IEEE Transactions on Instrumentation and Measurement*, DOI: 10.1109/TIM.2020.3018568, 2020.
[12] L. I. Hatledal, Y. Chu, A. Styve, and H. Zhang, "Vico: an entity-component-system based co-simulation framework", Simulation Modelling Practice and Theory, vol. 108, DOI: 10.1016/j.simpat.2020.102243, 2021.
[13] Open Simulation Platform. Open simulation platform, Joint industry project for the maritime industry. 2020. URL https://opensimulationplatform.com/ (Date accessed 5-April-2022).
[14] G. Moslått, D. Padovani, M. R. Hansen, "A Digital Twin for Lift Planning with Offshore Heave Compensated Cranes", Journal of Offshore Mech. Arct. Eng. June 2021, 143(3): 031402 (11 pages).
[15] S. Li, J. Liu, R. R. Negenborn and Q. Wu, "Automatic Docking for Underactuated Ships Based on Multi-Objective Nonlinear Model Predictive Control", in IEEE Access, vol. 8, pp. 70044-70057, 2020, doi: 10.1109/ACCESS.2020.2984812.
[16] L. R. Rodrigues, J. P. P. Gomes, F. A. S. Ferri, I. P. Medeiros, R. K. H. Galvão and C. L. Nascimento Júnior, "Use of PHM Information and System Architecture for Optimized Aircraft Maintenance Planning", in IEEE Systems Journal, vol. 9, no. 4, pp. 1197-1207, Dec. 2015, doi: 10.1109/JSYST.2014.2343752.
[17] Z. Xiao, Z. Cheng and Y. Li, "A Review of Fault Diagnosis Methods Based on Machine Learning Patterns", 2021 Global Reliability and Prognostics and Health Management (PHM-Nanjing), 2021, pp. 1-4, doi: 10.1109/PHM-Nanjing52125.2021.9612779.
[18] P. Han, A. L. Ellefsen, G. Li, F.T. Holmeset, H. Zhang, "Fault detection with LSTM-based variational autoencoder for maritime components", *IEEE Sensors Journal*, vol. 21, no. 19, pp. 21903-21912, DOI: 10.1109/JSEN.2021.3105226, 2021.
[19] S. Hochreiter. and J. Schmidhuber, "Long short-term memory". *Neural computation*, vol. 9, no. 8, pp. 1735-1780, DOI: 10.1162/neco.1997.9.8.1735, 1997.
[20] D. Welton and W. Knapek, "Important Considerations for Testing and Commissioning Digital Protective Relays: Avoid Misoperations", in IEEE Industry Applications Magazine, vol. 25, no. 4, pp. 24-28, July-Aug. 2019, doi: 10.1109/MIAS.2018.2875182.

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