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RESEARCH

Hybrid modelling–based digital twin for health monitoring in the naval auxiliary industry

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Abstract

Digital Twin (DT) technology is increasingly recognized for its potential to enhance product lifecycle management, operational efficiency, and data-driven decision-making across multiple industrial sectors. Although its adoption is growing in fields, such as aerospace and shipbuilding, its application within the Naval Auxiliary Industry—comprising the systems and suppliers that support core naval platforms—remains limited. This paper presents key insights from the TWIN NAVAUX project, which promotes the integration of digital twin technologies within this sector in the Galicia–North Portugal Euroregion. Based on demonstrator and real-world use cases, the study identifies major technical and organizational challenges, including system integration, data interoperability, and the inherent complexity of modelling ships as systems-of-systems (SoS). The work also outlines the essential building blocks required for successful DT deployment, such as standardized communication protocols, robust data acquisition and storage infrastructures, and advanced modelling and simulation techniques. Overall, the findings provide a structured roadmap to support and guide future digital twin implementations in the naval auxiliary domain.

1 Introduction

The concept of the Digital Twin (DT) was first introduced by M. Grieves in 2002 as a digital counterpart to a physical product, with the aim of supporting Product Lifecycle Management (PLM) (Grieves 2002). Its practical application first emerged in the aeronautical sector, particularly through NASA and the U.S. Air Force (Tuegel et al. 2011), and has since expanded to other domains, including shipbuilding, where companies, such as Navantia, were early adopters (Silvera et al. 2020). In contrast, the Naval Auxiliary Industry, which encompasses the suppliers and systems that support primary naval platforms, has been slower to adopt digital twin technologies. To address this gap, the TWIN NAVAUX project was launched to explore and promote DT solutions tailored to this sector's specific technical and operational challenges.

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One of the main barriers to DT deployment in naval platforms is their complexity. Ships must be understood as systems of systems (SoS), following Maier's definition of a system whose elements retain operational and managerial independence (Maier 1999). In a typical ship, the ship management system controls numerous independent subsystems, often supplied by different vendors and governed by diverse and sometimes incompatible standards and communication protocols. Developing a comprehensive digital twin, therefore, requires each subsystem to have its own digital representation, integrated seamlessly into the overall ship model. Achieving this integration requires centralized monitoring, coherent system behaviour, and standardized formats for data exchange and storage. Beyond system integration, digital twins provide value throughout the lifecycle of naval auxiliary equipment. They support lifecycle management (Mauro & Kana 2023), enhance operator training (Mallam et al. 2019), serve as effective tools for product demonstration at industry events, and enable product reconfiguration based on knowledge derived from digital twins or digital shadows (Riesener et al. 2025).

A comprehensive literature review indicates that recent advances in artificial intelligence, data analytics, and digital twin technologies have significantly influenced ship maintenance strategies. Predictive maintenance models play a key role in mitigating failure risks and optimizing maintenance

schedules (Karatuğ et al. 2023; Lazakis et al. 2018). Changes in operating state can strongly affect maintenance parameters for ship machinery, with consequences for equipment failure, environmental safety, and economic loss. As onboard systems continue to grow in scale and complexity, even localized faults can trigger cascading failures. Reliable real-time fault diagnosis is, therefore, essential for navigation safety.

Four representative methodological frameworks are commonly used for fault diagnosis: model-based, data-driven, knowledge-based, and hybrid-based approaches. In reviewing the evolution of diagnostic methods, Huang et al. (2026) identify three major challenges: difficulties in data acquisition and class imbalance, limitations in sensing and onboard computing capacity, and reduced diagnostic reliability under coupled fault scenarios. Model-based methods rely on mathematical representations, while knowledge-based methods rely on knowledge representation and inference mechanisms; both can be grouped as physics-based approaches. However, relatively little literature addresses their application to onboard ship systems. Examples include Tran (2019), who used Simulink to model a diesel engine in a bulk carrier, and Islam et al. (2021), who used OpenFOAM for propulsion modelling.

In recent years, however, data-driven models have shown strong performance in fault diagnosis, anomaly detection, and predictive maintenance (Guo et al. 2026; Karatuğ et al. 2023; Kirketerp-Møller et al. 2025; Zhou et al. 2021). Machine learning and deep learning algorithms have demonstrated strong potential for health monitoring and failure prevention. Yet the lack of sufficient training data remains a major limitation. To address this, physics-based models are often used as synthetic data generators to improve the accuracy of data-driven methods (Mavroudis & Tinga 2025). Another way to overcome this limitation is through Physics-Informed Neural Networks (PINNs), which incorporate physical constraints directly into the training process by adding terms to the loss function that reflect the system's differential equations or empirical relations (Fang et al. 2026). Despite these advances, both physics-based and data-driven approaches continue to face limitations in prediction accuracy and practical deployment. Gaps remain particularly in data integration and cost optimization. To address these challenges, some researchers have adopted hybrid approaches that combine real-time sensor acquisition through IoT-based condition monitoring systems, predictive analytics and machine learning for failure forecasting, and cost–benefit analysis to evaluate the economic impact of adaptive maintenance strategies compared with traditional methods (Holovan et al. 2026; Wang et al. 2021).

Within the broad range of machine learning techniques, LSTM-based models, as well as MLP, LSTM, and GRU architectures, have been applied to fault prognostics and health monitoring in marine diesel engines and other onboard machines and equipment (Han et al. 2021; Hu et al. 2022; Lee et al. 2025; Zhang et al. 2022). Digital twins are increasingly used to simulate complex system dynamics through continuous data exchange between physical assets and their virtual models (VanDerHorn et al. 2022). Real-time sensor data enables virtual models to support condition monitoring and informed maintenance decisions (Moghadam & Nejad 2022). Rotating machinery, including gearboxes, motors, generators, pumps, and rotor shafts, represents a critical class of components for which reliability and maintenance are essential (Inturi et al. 2024). Among these, electric motors, as primary actuators across ship systems, illustrate how component-level DTs can serve as building blocks for system-level integration. Permanent Magnet Synchronous Motors (PMSMs) are representative of the modelling approaches used in DT development. High-fidelity PMSM models, often implemented with finite element method (FEM) software, such as ANSYS, Simcenter, or COMSOL, can simulate electromagnetic, thermal, and mechanical interactions in detail. However, they require extensive parameterization and significant computational resources, which limits their applicability in real-time ship operations. Data-driven models, in contrast, use historical and operational data to enable predictive analytics without detailed physical inputs (Lukman & Lee 2025). Hybrid approaches combine these strategies to balance accuracy and computational efficiency.

Although high-fidelity and hybrid models represent the state of the art, they remain difficult to deploy in auxiliary systems due to complexity, cost, and real-time constraints. The present work, therefore, adopts a simplified modelling approach, prioritizing ease of implementation, reduced computational demand, and suitability for on-board integration. This perspective reflects the practical needs of auxiliary suppliers, where lightweight DTs can still deliver substantial benefits in predictive maintenance, operational optimization, and component-level monitoring, while serving as scalable building blocks toward integrated ship-level digital twins.

The literature provides examples of auxiliary-system DTs that support this more pragmatic direction. Liu et al. (2024) developed a crane DT using co-simulation, replicating boat and ship motions via Functional Mock-up Units (FMUs). Similarly, Miao et al. (2024) created a DT for monitoring ship equipment, including fans and pumps, using PSO-SVM forecasting. These studies show that manufacturer-provided DTs, even at a simplified level, can form the foundation for higher-level system DTs, enabling predictive maintenance, performance optimization, and operational decision support.

DTs have also been used for failure diagnosis by comparing real-time operational data with their digital counterpart. For example, Fera and Spandonidis (2024) proposed

a real-time monitoring framework for a three-phase low-voltage squirrel-cage induction motor, simulated in MATLAB Simulink. Fault detection was achieved by computing the Mahalanobis distance between measured operational data and the DT model, with deviations beyond a threshold indicating potential faults. This approach demonstrates how relatively simple models can provide effective early fault detection and preventive maintenance. Recent advances in naval condition monitoring further underline the trade-offs between complexity and practicality. Sun et al. (2025), in their systematic review of shipboard fault monitoring, highlighted typical faults and model-based detection methods, including DTs. They emphasize the ongoing difficulty of balancing accuracy with real-time performance, particularly in multiphysics DTs involving CFD or FEM simulations.

This paper investigates the implementation of a hybrid digital twin for a marine winch in collaboration with an auxiliary maritime company, demonstrating the potential of integrating digital twin technologies into physical products for predictive maintenance and operational monitoring. In this work, the KNN algorithm is applied to the electric motor of a winch. KNN is well suited to machine health monitoring, because it is simple to implement, requires little training, and can be updated easily as new operating data become available. It works by comparing current sensor readings with stored examples of normal behaviour, making it effective for detecting deviations, identifying anomalies, and supporting condition monitoring in data-driven maintenance systems.

The DT approach presented in this paper aligns with the challenge of marine deployment complexity, showing how computationally efficient DTs can make digitalization feasible for auxiliary systems, while still contributing meaningfully to the broader goal of ship-wide digital twin integration. In summary, this work presents a novel hybrid modelling approach that combines a physics-based model and a data-driven model as the core simulation framework of a digital twin. Rather than using the physics-based model as a synthetic data generator, the model is encapsulated as an FMU and coupled with the data-driven KNN model to build an enhanced hybrid digital twin.

Digital twins have been developed at both the system and subsystem levels to support specific operational functions on ships. They provide the basis for fully digitalized vessels, enabling capabilities, such as Machinery Health Monitoring (MHM), Asset Efficiency Monitoring (AEM), Operational Performance Management (OPM), and Crew Assistance and Augmentation (CAA) (Madusanka et al. 2023; Mao et al. 2025). The TWIN NAVAUX project aims to promote DT adoption among auxiliary companies in the Galicia–North Portugal Euroregion. These companies, which supply machinery and components for ship auxiliary systems, can leverage DT technology to enhance their products with digital functionality. Through digital models, auxiliary manufacturers can contribute directly to AEM, MHM, OPM, and CAA, thereby reinforcing their strategic role in ship digitalization.

2 Use case: digital twin for winch systems

2.1 Presentation of the use case

As part of the TWIN NAVAUX project, a digital twin demonstrator of marine winches was developed in collaboration with Ferri, an auxiliary maritime company. The demonstrator illustrates the practical application of digital twin technologies in the marine auxiliary sector through the real-time monitoring of an asset to support condition monitoring. The demonstrator focuses on an electric winch used for a transfer bag crane on an offshore wind platform. Winches are critical subsystems in marine operations, where failures can result in operational downtime, increased maintenance costs, and safety risks. The development of a digital twin for such a system, therefore, shows how simplified, but functional DTs can provide predictive maintenance, operational monitoring, and decision support for auxiliary equipment manufacturers.

For model calibration, operational data were collected from electronic control sensors connected to a Siemens S7-1200 PLC during a series of test-bench experiments conducted under varying speeds and loads. These tests provided the parameters required to configure the DT. The dataset included both electrical variables, such as frequency, current, voltage, DC bus voltage, torque, and RPM, and the applied test load weight, ensuring a representative operational profile of the winch system.

During operation, the demonstrator replicates the real user experience. The operator controls the winch using a physical joystick, as in the actual crane, while a dedicated monitoring screen displays the outputs of the digital twin. The DT computes an ideal load trajectory, defined as a load moving exclusively in the vertical direction and influenced only by gravity, without external disturbances, such as wind, wave-induced motion, or structural instabilities. This approach is particularly suitable for cranes operating in stable positions under no-wind or low-wind conditions, where the load motion is predominantly vertical and external perturbations remain limited. Performance parameters derived from the model are continuously calculated and compared in real time with live sensor data acquired from the physical winch system. When significant deviations between the model predictions and the measured data are detected, the system generates fault notifications, enabling operators to identify anomalies at an early stage and thereby support preventive maintenance strategies.

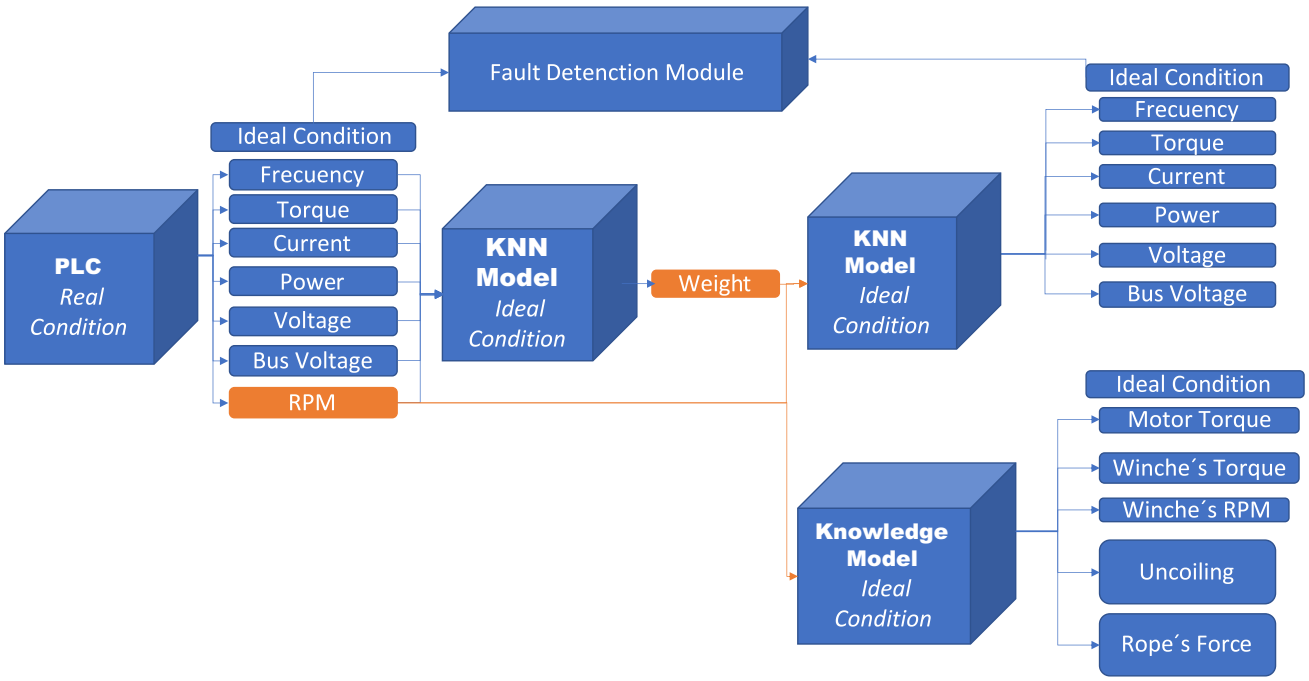


Fig. 1 Hybrid model architecture for winch system behaviour simulation

Table 1 Evaluation metrics obtained from different machine learning (ML) models that have been tested

	KNN average	XGB average	GB average	RF average	SVR average
R2	0,92	0,87	0,86	0,86	0,73
RMSE	10,56	18,59	18,78	18,78	24,62
MAE	4,40	6,66	6,74	6,39	11,37
RAE	0,16	0,18	0,18	0,18	0,31

2.2 Simulation model, a hybrid model approach with fault detection module

The Digital Twin for the winch system employs a hybrid modelling approach, combining physics-based simulation for mechanical components and data-driven machine learning models, in this case KNN, for electrical behaviour (Fig. 1). This approach balances computational efficiency with predictive accuracy, enabling real-time monitoring and anomaly detection while remaining feasible for on-board deployment. This approach provides a balance between computational efficiency and predictive accuracy, enabling real-time monitoring and anomaly detection while remaining suitable for deployment in on-board operational environments.

2.3 Electrical subsystem modelling

The electrical and control subsystems were modelled using data-driven algorithms. To select the most suitable approach, several candidate models, including Gradient Boosting (GB), Extreme Gradient Boosting (XGB), Support Vector Regression (SVR), K-Nearest Neighbours (KNN), and Random Forest (RF), were evaluated. Speed and load weight were used as input variables, while Weight [kg], Frequency [Hz], Torque [Nm], Current [A], Voltage [V], and Drive DC bus voltage [V] were considered as output variables. Among the evaluated models, KNN achieved the best performance under the operating conditions considered in this study. Nevertheless, these results should be interpreted with caution, as the models were trained and validated exclusively within the specific range of speeds and weights corresponding to the intended operating envelope. Consequently, the reported performance reflects interpolation within the training domain and should not be regarded as representative of predictive capability outside this range.

The evaluation metrics (R^2, RMSE, MAE, and RAE) were selected to assess both the correlation between predicted and measured values and the magnitude and distribution of prediction errors Table 1. These metrics, therefore, provide insight not only into the average accuracy of the models, but also into the consistency and dispersion of their predictions.

Table 2 Input and output parameters of KNN algorithm

	KNN1	KNN2
Inputs	measured electrical parameters (voltage, current, bus voltage) and RPM	estimated load (from KNN1) and RPM
Outputs	estimated mechanical load on the winch	predicted ideal electrical parameters (voltage, current, frequency) under normal operation

This evaluation strategy is aligned with the practical objective of achieving reliable real-time control and fault detection within the offshore platform system.

Therefore, the electrical and control subsystems are modelled using two K-Nearest Neighbours (KNN) algorithms trained on operational data collected from the PLC and test-bench experiments. The first model (KNN1) estimates the load on the winch, and the second model (KNN2) predicts the electrical parameters. KNN1 translates electrical behaviour into mechanical insights, enabling indirect observation of load variations without direct force sensors. KNN2 provides a reference model of the expected electrical behaviour under nominal conditions, so that deviations to signal potential faults (Table 2).

Model development was based on experimental training data collected at the Ferri facilities, where the available lifting infrastructure, calibrated weights, and experienced operators enabled controlled testing under realistic operating conditions. The experiments were conducted using a 7 m lifting structure, in which loads of 100, 300, 440, 735, and 845 kg were raised and lowered at approximately 25%, 50%, 75%, and 100% of the maximum operating speed. This procedure allowed the dataset to capture nonlinear load–response behaviour, operator-induced variability, and practical equipment constraints representative of real operation. The resulting dataset spans the nominal operating range of the crane, from 0 to 900 kg, and consists of 1,970 samples. The recorded variables include speed (RPM), frequency (Hz), torque (Nm), current (A), power (W), voltage (V), drive DC bus voltage (V), and weight (kg).

To preprocess the measured signals, a constant-velocity Kalman filter with a two-component state vector, ([signal_value, velocity]), was applied. In this formulation, the velocity term represents the temporal rate of change of each signal. The filter was independently applied to six raw electrical signals: output frequency, actual torque, actual current, output power, output voltage, and drive DC bus voltage. Each scalar measurement was processed sequentially to capture the smooth dynamic behaviour of the crane motor while attenuating high-frequency noise originating from the electric drive system and electromagnetic interference. The filter parameters were empirically tuned using a moderate measurement noise covariance of approximately ($R \approx 10$), consistent with an estimated sensor noise level of around 10% in the crane drive instrumentation, together with a low process noise covariance defined as $Q = 0.05 \cdot I$. This configuration enables the filter to track smooth system dynamics while preserving relevant transient responses. The state transition and observation matrices follow the standard one-dimensional constant-velocity model.

These models can estimate a range of key performance indicators from user-defined input parameters, providing the key variables needed to model the winch. Their accuracy was assessed using statistical metrics and cross validation. The performance of the KNN models is summarized in Table 3. The evaluation criteria include R^2**,** RMSE (Root Mean Squared Error)**,** MAE (Mean Absolute Error)**,** and RAE (Relative Absolute Error)**.**

This work adopts a multi-tier validation strategy aligned with established best practices in machine learning, incorporating nested cross-validation for hyperparameter tuning and stability assessment, strict data separation procedures, and real-world validation against live machine data. To determine the optimal number of neighbours (k) for the KNN models, GridSearchCV from the scikit-learn library was employed. This tool performs an exhaustive search over a predefined hyperparameter space using cross-validation to evaluate each candidate configuration. During hyperparameter selection, GridSearchCV executed an exhaustive fivefold cross-validation procedure considering values of $k = 1$—20 exclusively on the training dataset. For each value of (k), the model was trained on four of the five folds and validated on the remaining fold, with the performance averaged across all five rotations. This methodology provides a robust estimation of the mean squared error (MSE), reduces the risk of overfitting, and ensures that the selected hyperparameter generalizes consistently across all six output variables. To further assess model robustness, an additional fivefold K-Fold cross-validation procedure was performed after the optimal (k) value had been selected. In this stage, the model was evaluated using the optimal hyperparameter configuration to verify performance stability and low variance across folds. Evaluation metrics, including R^2, RMSE, MAE, and RAE, were computed for each fold and for all output variables. Preprocessing operations were applied independently within each fold to prevent data leakage. The resulting mean ± standard deviation values confirmed the stability and consistency of the model performance. A strict train–test separation strategy was also maintained throughout the study. The dataset was divided using a 70/30 split, with the training set (70%, fixed random_state = 100) used exclusively for hyperparameter tuning and cross-validation procedures, while the test set (30%) remained completely unseen until the final evaluation

Table 3 Metrics performance of KNN algorithms, being [U] the variable unit and[-] non-dimensional

Model	KNN1	KNN2					
Metric	Weight [Kg]	Frequency [Hz]	Torque [Nm]	Current [A]	Power [W]	Voltage [V]	Drive DC bus voltage [V]
Value range [U]	100 to 835	−82 to 73	−100 to 100	0 to 11	−6830 to 6050	0 to 506	519 to 831
R^2[-]	0,88	0.989	0.913	0.793	0.906	0.980	0.927
RMSE[U]	91,35	3.008	9.152	1.247	460.334	17.474	21.934
MAE [U]	33,71	0.965	4.296	0.532	154.281	6.929	9.280
RAE [-]	0.15	0.049	0.171	0.280	0.154	0.064	0.145

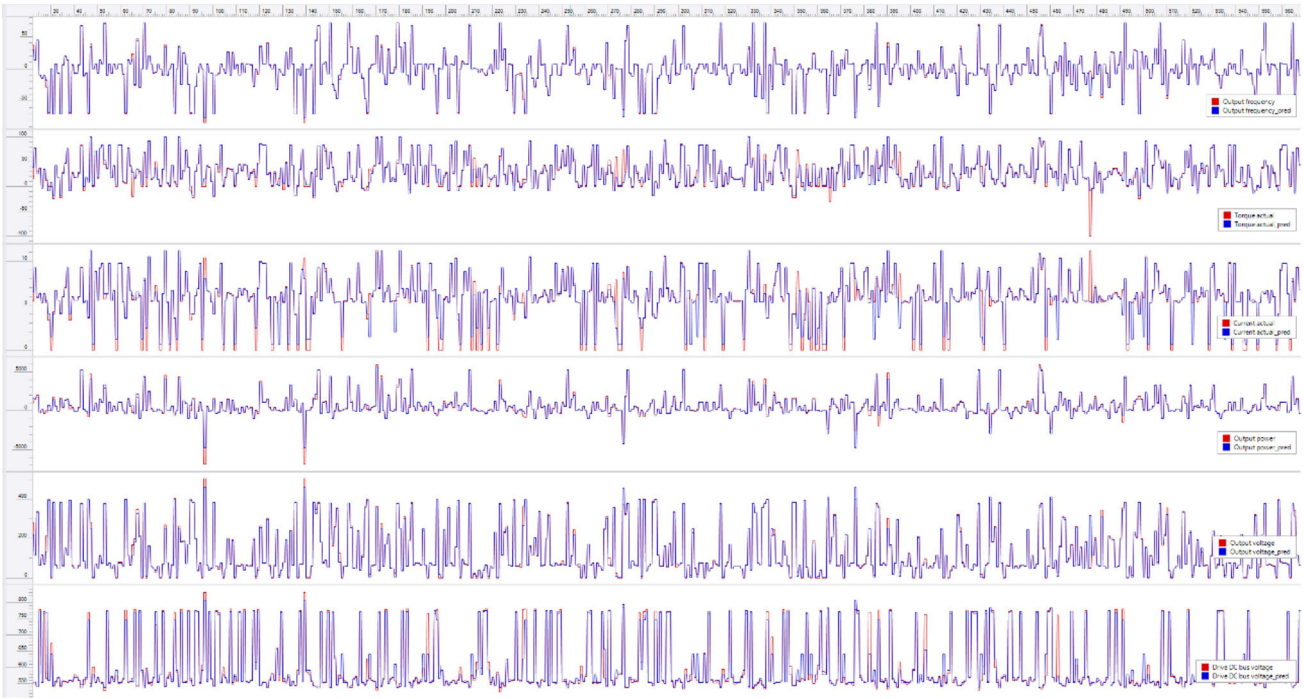


Fig. 2 Comparison between real data (red) and predicted data (blue) obtained in the cross-validation tests for frequency, torque, current, power, voltage, and drive DC-bus voltage, ordered from top to bottom

stage. Consequently, no information from the test set influenced model development or parameter selection.

Finally, validation was extended to the operational use case through a direct comparison between hybrid simulation outputs and real-time machine data acquired from the winch system. This comparison constituted the primary mechanism for dysfunction detection within the offshore platform control framework. The corresponding relative errors are presented in Table 5 of the Results section.

The predictive performance of the models was evaluated across multiple output variables, with KNN1 used for Weight and KNN2 applied to Frequency, Torque, Current, Power, Voltage, and Drive DC bus voltage. KNN1 achieved good accuracy for Weight ($R^2 = 0.88$, RMSE = 91.35, MAE = 33.71, RAE = 0.15), capturing the overall trend despite the relatively wide value range. KNN2 showed strong performance for the remaining variables, with Frequency ($R^2 = 0.989$), Power ($R^2 = 0.980$), and Voltage ($R^2 = 0.927$) exhibiting excellent agreement between predicted and measured values. Predictions for Torque ($R^2 = 0.913$, RAE = 0.280) and Current ($R^2 = 0.793$, RAE = 0.154) are less precise, indicating higher variability in these outputs. Overall, both models outperform a naive mean-based reference, and future work should focus on expanding the training data and refining the feature set to improve prediction accuracy for variables with higher relative errors, particularly Torque and Current.

Figure 2 shows how the KNN algorithm reproduces the normal operational behaviour of the electrical motor.

2.4 Mechanical subsystem modelling

The mechanical components of the winch, including the drum, gearbox, and rope dynamics, are represented using a physics-based model implemented in Simcenter Amesim. The model simulates Torque transmission through the gearbox, drum rotation as a function of the applied load and motor torque, rope tension and uncoiling dynamics, including acceleration and deceleration effects, and interactions under varying load conditions, such as hoisting or lowering different weights. This level of detail ensures that mechanical variables, such as torque and winch RPM are simulated accurately in real-time, forming a physical backbone for the hybrid model.

The mechanical winch system is represented in Simcenter Amesim as an ideal two-dimensional mechanism constrained to translational motion, composed by the gearbox, winch rope and mass. The mass value and winch RPM are obtained from the physical winch, and the weight is provided by the KNN1 model (Fig. 3). Rotational and out-of-plane dynamics are neglected, under the assumption that only gravity and applied torque act on the winch and that accelerations are low. The sheave radius is maintained as a constant throughout the simulation.

Several modelling assumptions were adopted. The winch is assumed to operate ideally, with no mechanical losses, slip, or rope compliance, and the motion is restricted to a planar and translational plane, with other motion components considered negligible. External loads are limited to gravity and applied torque, and the angular position of the sheave is obtained by integrating its angular velocity. The translational rope velocity at the winch is defined by an ideal gear mechanism, defined by a fixed ratio. This gear connects the electric motor and the winch shaft, scaling velocity, angular displacement, and torque under the assumption of a fully efficient and rigid transmission. Rope length variation is determined by the displacement of the sheave.

The metal rope is modelled as a longitudinal element that incorporates axial stiffness, internal viscous friction, gravitational effects, and inertia, with inertia governed by the number of discretization nodes. With zero nodes, which is appropriate for metal ropes, this model reduces to a spring-damper formulation suitable for quasi-static or mass-insensitive behaviour. Compression mode is set to normal, so the force remains unchanged when the rope enters compression. Rope parameters, such as stiffness, viscous friction, and mass, are specified per unit length and are dynamically adjusted during the simulation to account for initial tension settings and changes in rope geometry. The effect of gravity is calculated from the rope inclination, and local loading is distributed along the rope accordingly. Table 4 provides the mechanical model parameters.

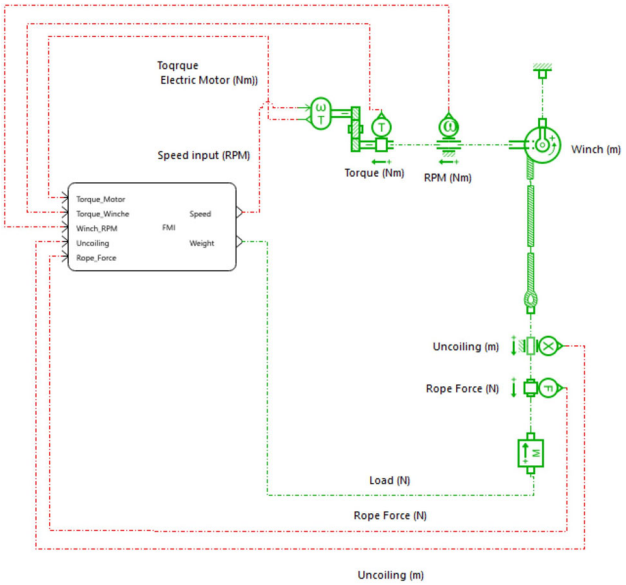


Fig. 3 Amesim mechanical system diagram showing the main components of the winch system and the corresponding FMU representation. The figure also illustrates the input and output variables associated with the FMU

Table 4 Mechanical model parameters

Parameter	Value	Units
Gear Ratio	55	
Winch Drum Diameter	290	mm
Winch Width Diameter	240	mm
Rope material	Steel	
Nodes number	Zero	
Compression type	Normal	
Rope inclination	0	Degrees

The simulation model is equipped with strategically placed virtual sensors at critical points to monitor essential physical quantities. These measurements are fundamental for evaluating system performance, supporting control strategies, and validating model fidelity. The simulated sensor data can be visualized with real-time graphical plots, organized in tabular form for detailed inspection, or archived in a database for post-processing. In this implementation, the virtual sensor measurements serve as output variables of the Functional Mock-up Unit (FMU), providing direct interface capability for performance analysis and functional integration.

The sensors defined within the simulation model are described as follows:

1. Torque sensor. This sensor measures the torque transmitted in the shaft downstream of the mechanical gear,

expressed in Newton-meters (N·m). In this framework, the torque value represents only the mechanical effort required to overcome the external load, such as cable tension and friction, under the imposed rotational speed. It does not include the internal losses or electromagnetic effects of the motor, but provides an accurate indication of the mechanical load transfer for efficiency analysis and structural evaluation.

2. Rotary Speed Sensor. This sensor records the rotational speed of the shaft downstream of the mechanical gear, expressed in revolutions per minute (RPM). Such measurements are critical for assessing dynamic performance, verifying speed-control algorithms, and correlating mechanical output with torque data.
3. Displacement Sensor. This device measures the linear displacement of the rope as it uncoils, expressed in meters (m). This parameter is used to evaluate the extent of rope deployment, monitor system kinematics, and provide reference data for motion control strategies.
4. Force Sensor. This sensor measures the tensile force acting on the rope, expressed in Newtons (N). The measurement is crucial for assessing structural loads.

2.5 FMU migration

The Functional Mock-up Interface (FMI) is an open standard that enables interoperability between models created in different modelling and simulation tools. FMI defines the Functional Mock-up Unit (FMU) format, a standardized package that encapsulates both a model and the required information for its simulation. Two operation modes are supported: Model Exchange, where the FMU provides only the mathematical representation of the model and delegates numerical integration to the host environment, and Co-Simulation, in which the FMU embeds its own solver and simulation algorithm.

In the present case study, simulations will be conducted in a Python-based environment using the FMPy library as the execution framework. FMPy is an open-source Python library developed by Dassault Systems for loading and inspecting FMUs with FMI 1.0 and FMI 2.0 standards.

In this work, the FMU is exported as a Co-Simulation model generated in Simcenter Amesim using the FMI version 2.0, as shown in Fig. 3. In this configuration, the FMU contains its own solver, requiring only coordination and data exchange through Python and FMPy.

Encapsulation is necessary to deploy the digital twin on a server, where a basic Simcenter Amesim license is used to run the solver.

2.6 Fault detection logic

The digital twin continuously compares real-time PLC measurements with the predicted ideal values from KNN2 using two complementary detection mechanism:

1. Instantaneous Check. This check detects anomalies by comparing the measured current and power values with their predicted counterparts. Because current and power are interdependent, an alert is triggered only when both variables deviate significantly from their predictions, thereby reducing false positives. A deviation threshold of $\pm$ 50% is used. This $\pm$ 50% threshold was selected heuristically to ensure that residuals observed during normal operating conditions remain within the acceptable range, while still enabling the detection of significant faults, such as overcurrent conditions or abnormal torque spikes. If the difference between the measured and predicted value exceeds this threshold for both variables, the system flags a potential fault. This method provides a fast, real-time mechanism for identifying abnormal operating conditions and helps ensure that alerts correspond to genuine system failures rather than transient noise or mirror fluctuation. (Fig. 4).

$$\text{If} \left| y_i - \hat{y}_i \right| > 0.5 \cdot \hat{y}_i, \text{ alert}$$

2. Moving Average Check. The relative absolute error (RAE) is accumulated over the last N measurements to detect abnormal conditions that develop gradually. The moving average of the RAE is computed as

$$RAE_N = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - \widehat{y_i}|}{|y_i|}$$

where y_i is the measured value, $\widehat{y_i}$ is the predicted value and N is the number of recent measurements.

If the moving-average RAE exceeds the predefined thresholds for a given variable, determined from historical data or system tolerance, an alert is raised, indicating a deviation from expected operational behaviour. The moving-average thresholds were heuristically derived from historical operational data and system tolerance considerations. The averaging window was designed to absorb minor short-term fluctuations, while allowing persistent deviations associated with slowly developing anomalies, such as gradual voltage degradation or efficiency drift, to consistently exceed the threshold and generate an alert. In the present implementation, the moving-average threshold for each variable was defined as the corresponding relative absolute error (RAE) increased by 10%. The heuristic thresholds ($\pm$ 50%, RAE + 10%) are preliminary. For operational deployment, statistical calibration (e.g., using 3-sigma or percentile limits from nominal data) is recommended. However, given that

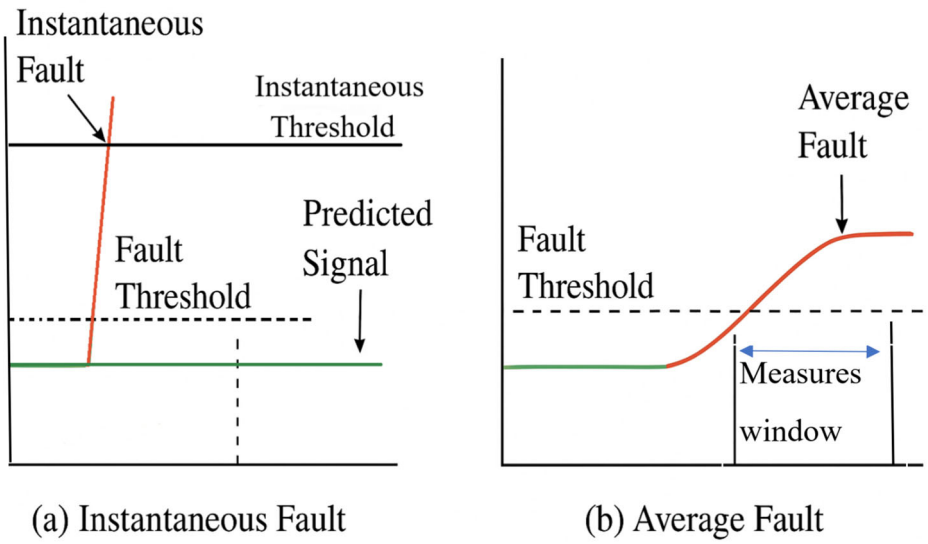


Fig. 4 Representation of the threshold used for anomaly detection

this is a methodology/demonstrator paper (not a clinical or safety–critical system), and the authors have clearly stated limitations and future work, these remaining issues are not fatal.

This dual approach enables the digital twin to detect both sudden faults, such as overcurrent or torque spikes, and slow-developing anomalies, such as gradual voltage drift, providing actionable insights for predictive maintenance and real-time operational decision support.

In the web application developed for this winch digital twin, the system status is represented by a five-digit error code (XXXXX), in which each digit corresponds to a parameter in the following order: frequency, torque, current, Power, and voltage]. Each digit indicates the condition of the corresponding parameter, according to the following convention: 0 denotes no error, 1 denotes an instantaneous fault, 2 denotes an Average fault, 9 denotes no data were received.

For example, the code 12,009 indicates an instantaneous fault in frequency, an average fault in torque: normal operation for current and power, and missing data for voltage.

The proposed approach is primarily oriented toward fault detection, while fault diagnosis still relies on the expertise and operational experience of the human operator. In this context, the operator is responsible for interpreting the detected anomalies, assessing their possible causes, and determining the appropriate corrective actions. Nevertheless, the system supports decision-making by facilitating error identification, assisting in maintenance planning, and enabling timely corrective interventions when required.

2.7 Digital twin deployment

The successful implementation of a digital twin requires bidirectional integration of the physical system with its virtual counterpart to ensure synchronized behaviour and reliable representation. In this work, such integration is achieved through a Python-based algorithm that acquires information from both the physical winch and the digital model. The physical winch data are collected via its Programmable Logic Controller (PLC) and include operational variables, such as run status, joystick speed reference, frequency, actual speed, torque, current, power, and voltage, including DC bus voltage. Among these variables, the actual speed is particularly important, as it allows the digital twin to be directly driven by the physical joystick of the winch.

To initialize the models and start winch operation, the following sequence is performed (Fig. 5):

1. The operator sets the winch RPM via the joystick.
2. Based on PLC parameters, the KNN1 model estimates the load weight.
3. Using the calculated weight and RPM, the KNN2 model determines the electrical parameters, while the FMU corresponding to the Amesim model computes the mechanical parameters.
4. The diagnostic module compares real and simulated winch behaviour to detect malfunctions and faults.
5. Real data and simulated data are stored in the server in SQL databases with each record generating 809 bytes every 2 s, or approximately 404 bytes per second. This results in database growth of approximately 1.4 MB per hour and 34 MB per day during continuous operation.
6. The data are sent to a web application for visualization and analysis, and to a 3D model integrated in an AR

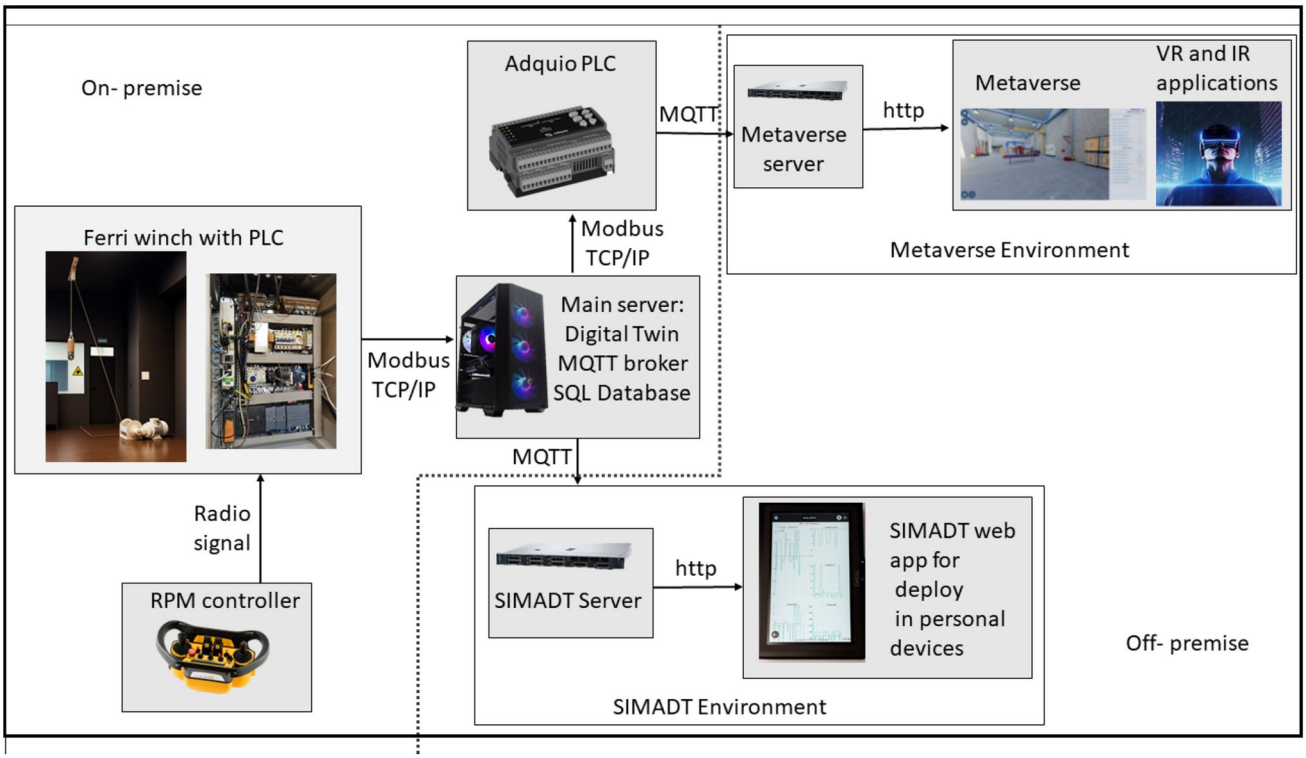


Fig. 5 System Architecture Diagram with Service Integration

environment, which can be used for training, operation monitoring, and marketing purposes.

The entire digital twin operates on a Windows 11 workstation equipped with an Intel Core i7-13700F processor and 1 TB of memory, ensuring smooth real-time data processing, simulation execution, and visualization without computational bottlenecks. This configuration maintains dynamic coherence between physical operation and virtual simulation, thereby enhancing both fidelity and usability.

The deployment architecture of the proposed Digital Twin (DT) framework was designed to support real-time monitoring and anomaly detection while remaining computationally efficient enough for practical on-board implementation in naval auxiliary systems. At the core of the system, the Functional Mock-up Unit (FMU) encapsulates the physics-based mechanical model of the winch subsystem developed in Simcenter Amesim. The FMU receives operational inputs, such as load weight and motor speed, and generates the expected mechanical response of the system under nominal operating conditions. Because the FMU is exported as a standardized functional unit, it can be integrated independently of the original modelling environment, improving portability and interoperability within the DT framework.

In parallel, the data-driven layer, implemented using the KNN algorithm, processes live electrical and operational measurements acquired from the physical asset. These measurements include variables, such as current, voltage, frequency, torque, and drive DC bus voltage. Prior to inference, the raw sensor data are filtered using a Kalman-based preprocessing stage to attenuate noise and stabilize signal dynamics. The processed data are then compared against historical operational patterns learned during the training phase.

Both subsystems are integrated through a supervisory co-simulation architecture. The FMU continuously generates reference operating values, while the KNN model evaluates whether the measured behaviour remains consistent with previously observed normal operating conditions. Residuals between predicted and measured signals are computed in real time, and threshold-based logic is used to identify persistent deviations associated with abnormal or overload conditions.

From a deployment perspective, the architecture was intentionally designed to minimize hardware and infrastructure requirements. One of the main advantages of the proposed DT is that it relies exclusively on data already available from the existing crane control system, without requiring additional sensors or modifications to the machine architecture. This makes the framework particularly suitable for retrofit applications in existing naval auxiliary equipment.

The DT operates locally within the platform environment, avoiding continuous dependence on cloud infrastructure and

reducing latency for real-time monitoring tasks. The local deployment approach also improves operational robustness in offshore environments where network connectivity may be intermittent or limited. In the current implementation, the operator remains part of the decision-making loop, reviewing alarms and determining corrective actions when anomalies are detected.

The modular nature of the architecture also facilitates future scalability. Additional machine-learning models, sensing technologies, or communication layers could be incorporated without redesigning the entire framework. Likewise, cybersecurity mechanisms, such as encrypted MQTT communication protocols, can be integrated in future connected deployments to support secure industrial IoT operation.

The proposed integration framework offers three main advantages:

- Real-time system characterization, through continuous acquisition and synchronization of operational data between the physical and digital domains.
- Fault detection and diagnosis, through systematic comparison of empirical measurements with simulated outputs to identify anomalies relative to the nominal operating state.
- Broad applicability, enabling technology demonstrations without the physical asset, remote operation monitoring, and immersive operator training.

In addition, the system includes a demo mode for training and demonstration purposes, capable of simulating two types of faults. The first is an instantaneous overcurrent scenario, in which power, current, and torque increase gradually while the motor is running, with power ramping over time to a defined maximum. Torque is recalculated based on power and motor speed. The second is a block/lock scenario, in which the motor stops suddenly, where speed drops to zero, voltage decreases, and current/power spike occurs. In this case, torque and current increase progressively to simulate mechanical blocking or stall. Both scenarios dynamically update system parameters in real time, providing a safe environment for studying motor responses under fault conditions.

To improve access to digital twin health monitoring and fault diagnostics, a dedicated web application named SIMADT (Smart Interface for Marine Assets Digital Twins) was created. This platform enables operators to monitor the operational performance of multiple winches in real time and review historical time-series data. SIMADT supports both actual sensor data and simulated data, facilitating analysis of potential fault trends for improved asset reliability and maintenance decision-making.

For the real-time visualization, data are sent via MQTT from the main server to the service providers, from where the services are published as web applications deployable on different devices, including personal devices, desktops and VR glasses, as shown in Fig. 5.

3 Results and validation

The system was validated under controlled operating conditions, demonstrating robust performance and a strong correlation between the experimental results and the digital twin predictions, as illustrated in Fig. 6. The hybrid model achieved a correlation coefficient of 0.9, effectively capturing the nonlinear interactions between electrical and mechanical parameters. This level of agreement supports the model's suitability for reliable fault detection, as described above.

The validation scenario was conducted at the company's facilities, where the winch digital twin was assessed under controlled operating conditions designed to reproduce representative variations in load, speed, and voltage while comparing measured sensor data with the twin outputs in real time. Validation commenced under nominal operating conditions to establish baseline agreement, after which predefined disturbances, including overload, torque fluctuation, and temporary signal loss, were introduced to evaluate the model's ability to detect deviations consistently and distinguish normal behaviour from incipient faults. The scenario further included repeated trials across different operating regimes to verify robustness throughout the expected range of winch operation, with error metrics, correlation values, and fault-detection latency recorded throughout the tests. This validation approach demonstrated both the accuracy of the hybrid model and its practical suitability for condition monitoring, anomaly detection, and maintenance support in realistic marine auxiliary applications.

To evaluate the fault-detection capability of the system, an overload condition was intentionally simulated in the winch system. Figure 7 further shows one of this simulated overload scenario in which clear discrepancies between measured data and digital twin outputs were generated and accurately identified by the fault detection module.

The hybrid simulation model yields result that remain within acceptable accuracy bounds for most measured variables, with relative errors of 9.4% for voltage, 5.8% for current, 12% for frequency, 12.5% for power, and 24.6% for torque (Table 5). These results demonstrate the model's capability to reproduce the coupled electrical–mechanical behaviour of the equipment with sufficient fidelity for the intended applications, while also indicating torque prediction as the main area for future improvement (Table 5).

The response speed of the system is fast, with the Functional Mock-up Unit (FMU) executing in real time at 100 Hz. This ensures timely processing and responsiveness, which are essential for real-time applications.



Fig. 6 Diagrams illustrating normal operating conditions for torque (N·m), current (A), and power (W) as represented in SIMA-DT. The real measured data is shown in yellow, while the predicted data is shown in blue

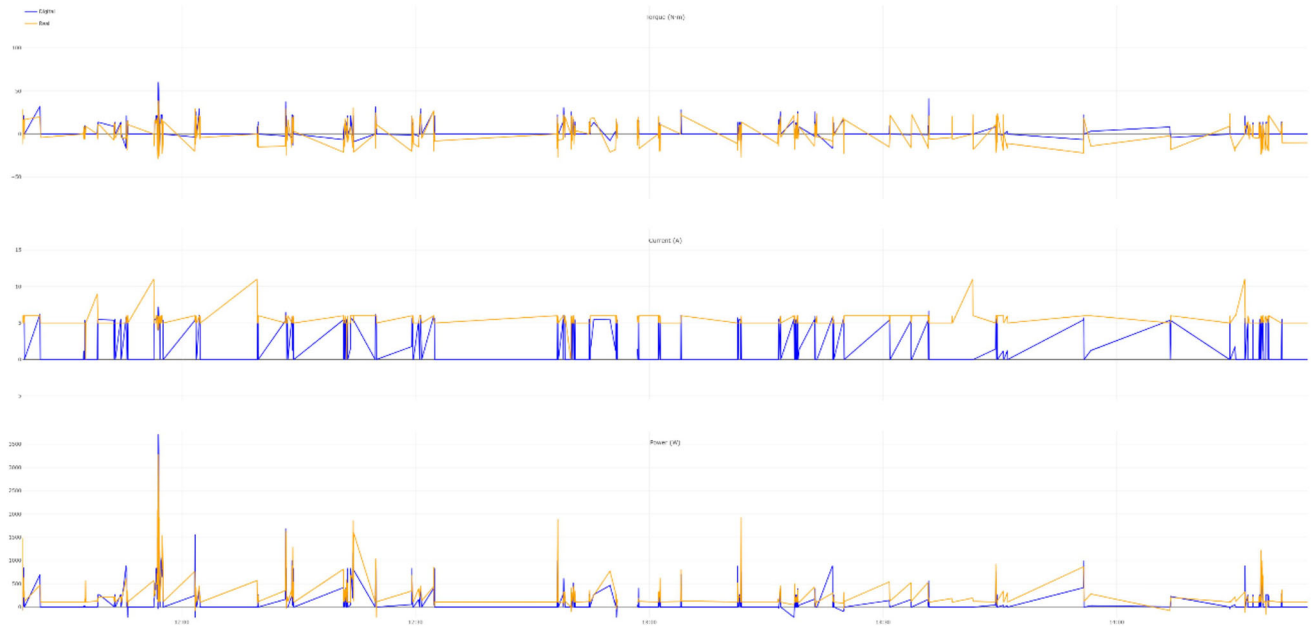


Fig. 7 Diagrams illustrating overload conditions for torque (N·m), current (A), and power (W) as represented in SIMA-DT. The real measured data are shown in yellow, while the predicted data is shown in blue

Table 5 Relative errors obtained in the main variables

Variable	Relative Error
Voltage	9,4%
Current	5,8%
Frequency	12%
Power	12,5%
Torque	24,6%

In terms of system stability, the implementation is robust, with no runtime crashes or loss of synchronization during operation. This stability is essential for maintaining reliable and consistent performance over extended periods in operating conditions.

From a qualitative perspective, the hybrid architecture demonstrates strong practical value because it preserves the main functional behavior of the equipment while remaining

computationally lightweight enough for near real-time use. The model can follow the general response of the system and detect meaningful deviations under abnormal conditions, which is essential for condition monitoring and fault detection. The correlation observed between experimental data and digital twin outputs confirms that the model captures the dominant system trends, even if it does not reproduce every transient effect with high precision. This is important because the goal of the implementation is not full physical replication, but rather operationally useful monitoring and early warning. In that sense, the model succeeds as a decision-support tool: it provides enough accuracy to distinguish normal from abnormal behavior and to identify when the system departs from expected operating patterns.

Quantitative fault detection metrics (e.g., false positive rate, true positive rate) were not calculated because the overload scenario was simulated and no physical fault injection was performed. This is a limitation of the current study.

Overall, the results support the usefulness of the proposed approach for marine auxiliary equipment monitoring, especially in environments where computational efficiency, ease of deployment, and practical interpretability are more important than exact numerical reproduction. The combination of acceptable electrical accuracy, strong correlation with measured behavior, and successful fault detection under overload conditions demonstrates that the system is suitable for operational digital twin applications. However, the relatively high torque error indicates that it could not be reproduced with the same level of accuracy as the other variables. This limitation is mainly attributed to the additional physical phenomena required for a more detailed torque representation, as well as the lack of sufficient system information to reliably identify and calibrate these effects. For this reason, the model was deliberately kept at a reduced level of complexity, and torque was not considered a critical variable within the hybrid digital twin framework (Table 6).

4 Conclusions and future work

The development and deployment of digital twin models for ship subsystems, particularly complex machinery integrating electric motors and electronic control systems, pose significant technical and organizational challenges. A primary limitation is the accurate representation of advanced equipment, which often requires detailed internal component information from original equipment manufacturers (OEMs). However, access to such proprietary data is typically restricted to protect intellectual property, thereby limiting the fidelity and transparency of purely physics-based digital twin models.

In this context, data-driven modelling approaches provide a practical alternative. By leveraging empirical operational data, these methods can reproduce system behaviour and enable functionalities, such as anomaly detection and predictive maintenance, based on observed performance patterns. Although data-driven models are relatively straightforward to deploy and effective in identifying symptomatic faults, their diagnostic capability is inherently limited. They lack the explanatory power of physics-based models and are highly dependent on data quality, operational variability, and dataset representativeness.

To overcome these limitations, hybrid modelling strategies that combine data-driven and knowledge-based approaches offer a balanced solution. Within the TWIN NAVAUX project, a hybrid digital twin was developed and validated, using its operational environment as the testbed. The demonstrator integrated data-driven models for the electric motor and control subsystems with a knowledge-based model for the mechanical subsystem. This architecture enabled a reliable reproduction of machine behaviour with sufficient accuracy for condition monitoring and maintenance support, while improving interpretability compared to purely data-driven solutions.

Therefore, the novelty of this work lies in the proposed hybrid digital twin architecture, which combines a K-Nearest Neighbours (KNN) model with a Functional Mock-up Unit (FMU) to integrate data-driven anomaly detection with physics-based simulation. Within this framework, the FMU represents the mechanical behaviour of the winch subsystem and generates the expected operational response under given input conditions. In parallel, the KNN model evaluates live sensor measurements against historical operational patterns to detect deviations from normal behaviour. The integration is organized through a co-simulation or supervisory architecture in which the FMU provides reference states

Table 6 Evaluation metrics obtained from different machine learning (ML) models that have been tested

	KNN average	XGB average	GB average	RF average	SVR average
R2	0.92	0.87	0.86	0.86	0.73
RMSE	10.56	18.59	18.78	18.78	24.62
MAE	4.40	6.66	6.74	6.39	11.37
RAE	0.16	0.18	0.18	0.18	0.31

and performance estimations, while the KNN layer classifies operating conditions and identifies abnormal states based on both electrical and mechanical features. This combined approach enables the system to benefit simultaneously from the interpretability and structural insight provided by the physics-based model and from the adaptability and simplicity of the data-driven method. As a result, the proposed framework offers a practical and effective solution for condition monitoring, anomaly detection, and maintenance support in naval auxiliary systems.

The developed model is constrained to the operating envelope of the test machine (0–900 kg), which defines the range of the training data. In addition, the physics-based subsystem assumes an ideal load motion restricted to the vertical direction under gravitational forces, neglecting external disturbances, such as wind effects or structural instabilities. This simplification is appropriate for stable crane operations under no-wind or low-wind conditions, where safety and controlled motion are prioritised. Nevertheless, limitations in root-cause fault isolation remain. The main inaccuracies in torque prediction are associated with the limited complexity of the electric motor model. As a result, physics-based torque estimations are not currently used for monitoring or fault diagnosis alone. This variable was deliberately kept as an auxiliary variable in the model, not critical, for fault diagnosis detection. Therefore, future improvements in fault-diagnosis capability could be achieved through high-fidelity simulation of fault scenarios or by integrating complementary sensing technologies, such as vibration, acoustics, thermal measurements, or motor current signature analysis. While these approaches would enhance fault isolation and detection accuracy, they would also increase system complexity and implementation cost.

Despite these limitations, a key advantage of the proposed framework is that it was developed using only data already available within the manufacturer's existing infrastructure, without requiring additional sensors, acquisition hardware, or modifications to the machine architecture. Consequently, implementation costs are mainly associated with deployment, computational resources, and periodic model updates. In industrial contexts, these requirements represent a relatively modest investment compared to conventional fault-diagnosis systems that rely on extensive additional instrumentation or redesign.

Overall, this study highlights the value of integrated modelling strategies for advancing digital twin technologies in the naval auxiliary domain. Complex machinery incorporating electric drives and electronic control systems benefits from the combination of data-driven and knowledge-based methodologies. Data-driven models provide flexibility by exploiting operational data, while knowledge-based models contribute structural understanding and interpretability, both of which are essential for robust and scalable digital twin deployment. The TWIN NAVAUX demonstrator, developed and validated at Ferri facilities using a marine winch system, confirms that hybrid architectures can reproduce real machine behaviour with meaningful accuracy and practical utility, particularly when supported by extensive, high-quality operational datasets.

A key future direction is the incorporation of adaptive learning strategies capable of responding to new operational conditions and system behaviours. Although KNN-based approaches are not inherently continuous-learning models and require periodic retraining, adaptation can still be achieved through batch updates using operational data collected during navigation. In this context, representative datasets must first be selected through appropriate filtering prior to retraining. However, alternative machine-learning approaches with stronger online-learning capabilities should be further explored to enable more robust, scalable, and adaptive digital twin frameworks for naval applications.

Another important aspect concerns cybersecurity and data protection. At present, the system operates locally under human supervision via the crane joystick and is not connected to the Internet. As a result, potential vulnerabilities are primarily related to data interception or theft rather than direct system manipulation. However, as digital twin architectures increasingly rely on connected infrastructures, cybersecurity becomes a critical requirement for future deployments. In this context, secure communication protocols, such as MQTT, combined with encryption mechanisms are actively being investigated in both academia and industry to mitigate vulnerabilities and enhance the reliability of industrial IoT and digital twin systems.

The proposed winch digital twin can be interpreted as a constituent system within a broader system-of-systems architecture, since it operates autonomously at the subsystem level while exchanging data and functionality with other onboard systems and management layers. Under this view, the winch DT is not an isolated model, but a modular digital asset that can support integration into a future platform-wide digital twin ecosystem. To architect the winch digital twin as part of a larger offshore platform system-of-systems, the cleanest approach is to treat the winch DT as an independent constituent system that exposes standard services to a system-level orchestrator, rather than as a tightly coupled module inside a monolithic platform. That preserves local autonomy for the winch model, while allowing the offshore platform SoS to aggregate status, coordinate maintenance, and optimize resources across multiple assets. So, above the winch DT level, an orchestrator layer is needed that subscribes to winch health events, maintenance requests, and performance summaries, then combines them with other asset twins for higher-level decisions.

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Author contribution A.V.D developed the software, and wrote the original draft. Hed did part of data curation as well. A.M.D. was the project administration, did the review and editing of the manuscript. She propose the methodology and did the validation. J.L.V. developed the visualization part and did the formal analysis.

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Data availability Data is under private company confidentiality.

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References

Fang T, Zheng H, Hong Y, Zhu X, Liu Y (2026) A physics-informed neural network approach for marine turbocharger performance evaluation in ocean-going vessels: under incomplete parameter conditions. Eng Appl Artif Intell 178:114918. https://doi.org/10.1016/j.engappai.2026.114918

Fera F, Spandonidis C (2024) A Fault Diagnosis Approach Utilizing Artificial Intelligence for Maritime Power Systems within an Integrated Digital Twin Framework. Appl Sci 14(18):8107. https://doi.org/10.3390/APP14188107

Grieves, M. (2002). *(PDF) SME Management Forum Completing the Cycle: Using PLM Information in the Sales and Service Functions*. https://www.researchgate.net/publication/356192963_SME_Management_Forum_Completing_the_Cycle_Using_PLM_Information_in_the_Sales_and_Service_Functions

Guo Y, Lang X, Wang Y, Zhang X, Zhao X, Fu S, Mao W (2026) State-of-the-art machine learning applications for ship performance modeling: a comprehensive review from design and operation to maintenance and retrofit. *Applied Energy*. Elsevier Ltd. https://doi.org/10.1016/j.apenergy.2026.127829

Han P, Ellefsen AL, Li G, Æsøy V, Zhang H (2021) Fault prognostics using LSTM networks: application to marine diesel engine. IEEE Sens J 21(22):25986–25994. https://doi.org/10.1109/JSEN.2021.3119151

Holovan A, Smieszek M, Gritsuk I, Mateichyk V, Honcharuk I, Mosciszewski J (2026) Adaptive maintenance strategies for cargo ships: digital approaches and cost optimization. Transp Res Procedia 93:162–167. https://doi.org/10.1016/j.trpro.2025.11.025

Hu Y, Miao X, Si Y, Pan E, Zio E (2022) Prognostics and health management: a review from the perspectives of design, development and decision. Reliab Eng Syst Saf. https://doi.org/10.1016/j.ress.2021.108063

Huang K, Li W, Cao S, Gao F, Li R, Xu W, Lin B (2026) Recent advances in fault diagnosis of ship integrated power systems: A review. Ocean Eng. https://doi.org/10.1016/j.oceaneng.2025.123141

Inturi V, Ghosh B, Rajasekharan SG, Pakrashi V (2024) A review of digital twinning for rotating machinery. Sensors 24(15):5002. https://doi.org/10.3390/S24155002

Islam H, Guedes Soares C, Liu J, Wang X (2021) Propulsion power prediction for an inland container vessel in open and restricted channel from model and full-scale simulations. Ocean Eng. https://doi.org/10.1016/j.oceaneng.2021.108621

Karatuğ Ç, Arslanoğlu Y, Guedes Soares C (2023) Design of a decision support system to achieve condition-based maintenance in ship machinery systems. Ocean Eng. https://doi.org/10.1016/j.oceaneng.2023.114611

Kirketerp-Møller T, Hyldgaard MW, Cai J, Dodis AI, Rytter NGM (2025) Data-driven predictive maintenance for two-stroke marine diesel engines using machine learning and MLOps. J Ocean Eng Sci. https://doi.org/10.1016/j.joes.2025.11.011

Lazakis I, Raptodimos Y, Varelas T (2018) Predicting ship machinery system condition through analytical reliability tools and artificial neural networks. Ocean Eng 152:404–415. https://doi.org/10.1016/j.oceaneng.2017.11.017

Lee S, Kim D, Yeom E (2025) Predictive maintenance using estimation from time interval for butterfly valves. Result Eng. https://doi.org/10.1016/j.rineng.2025.104609

Liu Z, Chu Y, Li G, Hildre HP, Zhang H (2024) Shipboard crane digital twin: an empirical study on R/V Gunnerus. Ocean Eng. https://doi.org/10.1016/j.oceaneng.2024.117675

Lukman GF, Lee C (2025) Towards Digital Twin Modeling and Applications for Permanent Magnet Synchronous Motors. Energies 18(4):956. https://doi.org/10.3390/EN18040956

Madusanka NS, Fan Y, Yang S, Xiang X (2023) Digital twin in the maritime domain: a review and emerging trends. J Marine Sci Eng. https://doi.org/10.3390/jmse11051021

Maier MW (1999) Architecting principles for systems-of-systems. Syst Eng (INCOSE) 1:267–284. https://doi.org/10.1002/(SICI)1520-6858(1998)1:4<267::AID-SYS3>3.0.CO;2-D

Mallam SC, Nazir S, Renganayagalu SK (2019) Rethinking maritime education, training, and operations in the digital era: applications for emerging immersive technologies. J Marine Sci Eng 7(12):428. https://doi.org/10.3390/JMSE7120428

Mao R, Li Y, Li G, Petter Hildre H, Zhang H (2025) A systematic survey of digital twin applications: transferring knowledge from automotive and aviation to maritime industry. IEEE Trans Intell Transp Syst 26(4):4240–4259. https://doi.org/10.1109/TITS.2025.3535593

Mauro F, Kana AA (2023) Digital twin for ship life-cycle: a critical systematic review. Ocean Eng 269:113479. https://doi.org/10.1016/J.OCEANENG.2022.113479

Mavroudis S, Tinga T (2025) Application of transfer learning on physics-based models to enhance vessel shaft power predictions. Ocean Eng. https://doi.org/10.1016/j.oceaneng.2025.120540

Miao Z, Zhao Y, Su S, Song N (2024) A digital twin comprehensive monitoring system for ship equipment. Pol Marit Res 31(4):111–121. https://doi.org/10.2478/POMR-2024-0055

Moghadam FK, Nejad AR (2022) Online condition monitoring of floating wind turbines drivetrain by means of digital twin. Mech Syst Signal Process. https://doi.org/10.1016/j.ymssp.2021.108087

Riesener M, Rebentisch E, Keuper A, Blondrath A, Weber P, Schuh G (2025) Design model for digital shadows to support reconfiguration decisions in manufacturing. Procedia CIRP 132:153–158. https://doi.org/10.1016/J.PROCIR.2025.01.026

Silvera JI, Luis J, José M, Luquero M, Bustelo M (2020) Navantia's digital twin implementation perspective in military naval platform life

cycle. https://publications.sto.nato.int/publications/STO%20Meeting%20Proceedings/STO-MP-MSG-171/MP-MSG-171-P1.pdf

Sun J, Sun P, Lin B, Li W (2025) Evolution of shipboard motor failure monitoring technology: multi-physics field mechanism modeling and intelligent operation and maintenance system integration. Energies (19961073) 18(16):4336. https://doi.org/10.3390/EN18164336

Tran TA (2019) Investigate the energy efficiency operation model for bulk carriers based on Simulink/Matlab. J Ocean Eng Sci 4(3):211–226. https://doi.org/10.1016/j.joes.2019.03.004

Tuegel EJ, Ingraffea AR, Eason TG, Spottswood SM (2011) Reengineering aircraft structural life prediction using a digital twin. Int J Aerosp Eng 2011(1):154798. https://doi.org/10.1155/2011/154798

VanDerHorn E, Wang Z, Mahadevan S (2022) Towards a digital twin approach for vessel-specific fatigue damage monitoring and prognosis. Reliab Eng Syst Safety. https://doi.org/10.1016/j.ress.2021.108222

Wang R, Chen H, Guan C, Gong W, Zhang Z (2021) Research on the fault monitoring method of marine diesel engines based on the manifold learning and isolation forest. Appl Ocean Res. https://doi.org/10.1016/j.apor.2021.102681

Zhang P, Gao Z, Cao L, Dong F, Zou Y, Wang K, Zhang Y, Sun P (2022) Marine systems and equipment prognostics and health management: a systematic review from health condition monitoring to maintenance strategy. Machines (Basel). https://doi.org/10.3390/machines10020072

Zhou Y, Dong Y, Zhou H, Tang G (2021) Deep dynamic adaptive transfer network for rolling bearing fault diagnosis with considering cross-machine instance. IEEE Trans Instrum Meas. https://doi.org/10.1109/TIM.2021.311280

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