

TRAVISIONS

TRA VISIONS 2024

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C2024 - 37

PILLAR / TRANSPORT MODE				
ROAD ☐	RAIL ☐	WATERBORNE ☒	AIRBORNE ☐	CROSS MODAL ☐
Project Related to:	☒ RA1: Safe & Inclusive Transport ☐ RA2: Sustainable Mobility of People & Goods ☐ RA3: Collaborative Digitalisation ☐ RA4: Efficient & Resilient Systems			

Project Title:

AI-based digital twin for safe and sustainable ship operations



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AI-based digital twin for safe and sustainable ship operations

Team: Intelligent and Sustainable Maritime Horizon (ISMH) C2024-37

1. Introduction

The development of artificial intelligence (AI) has been applied in various fields to improve the efficiency of society and industry. The shipping industry is also looking for opportunities to take advantage of AI. Although shipping plays a crucial role in global trade, accounting for over 90% of the transportation of goods worldwide ¹, shipping emissions matter for the environment ². The utilization of emerging techniques, such as AI and digital twin, to optimize ship maneuvering and fuel consumption is still in the early stages. As a result, there is a growing need to ensure the safety and sustainability of ship operations by embracing modern technology.

In this report, as shown in Figure 1, a multi-objective AI-based digital twin is introduced to represent a physical vessel by combining real-time data, deep learning models, and advanced analytics. The primary aim is to generate the optimal operational command for the presented ship by iterating distinct operational scenarios with the corresponding predicted operational command, enhancing the safety and sustainability of ship operations. To represent a physical vessel in real life, the digital twin encompasses two sub models by serving different purposes. Specifically, bi-directional Long Short-Term Memory (Bi-LSTM) with an attention mechanism is established to predict ship fuel consumption in real operational conditions, and a transformer neural network is built to estimate ship motion reflecting hydrometeorological conditions. Combining two sub modules, the digital twin can predict fuel consumption and ship motions by capturing operational features under actual complex conditions. Based on the fine-tuned digital twin, different navigational conditions can be collected based on nowcast weather data (i.e., wind, wave, current, etc.), and corresponding ship motions and fuel consumptions can be predicted. Subsequently, the best optional command (safe and sustainable ship manoeuvring command) can be figured out by iteration and comparison, as depicted in Figure 4. To demonstrate the effectiveness of the digital twin, sea trials data of a bulk carrier and Ro-Ro passenger ship is used. The results show that the digital twin can accurately represent the operational status of ships. It can generate the best operational command by iterating distinct operational scenarios.

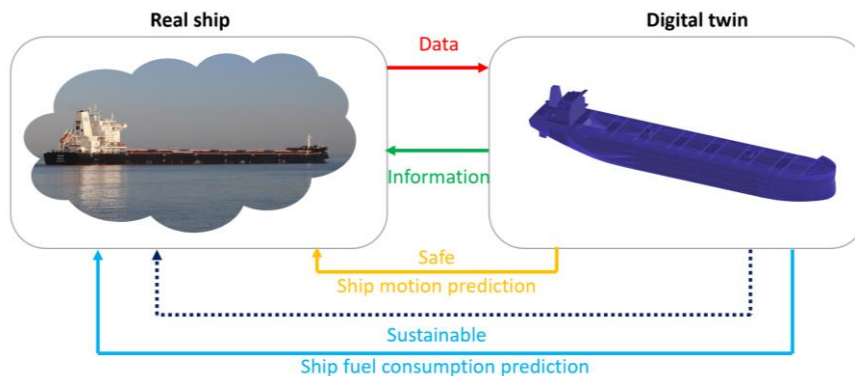


Figure 1. The ship digital twin for proactive optimization of ship operations.

The report is organized as follows. In Section 2, the selected research area is described. Section 3 describes the existing ideas related to the selected area and the gaps. Section 4 depicts how to use AI techniques to improve the safety and sustainability of ship operations. Section 5 describes the multi-objective AI-based digital twin in detail, demonstrates the proposed solution's effectiveness, and presents the practical application. Section 6 highlights and concludes the promising prospects of the AI-based digital twin in developing intelligent decision support systems for effectively monitoring and enhancing ship safety and sustainability.

2. Selection of research area

Shipping safety and efficiency are important due to the significant impact on global trade and environment. This report focuses on the safety and sustainability improvement for the shipping industry using AI techniques. Specifically, a multi-objective AI-based digital twin is proposed for safe and efficient ship operations. It addresses the need for more sustainable shipping practices without compromising safety standards.

- **Environmental Impact:** Given the requirement of decarbonization, maritime emission reduction attracts lots of attention. For the existing ships, fuel consumption reduction by optimizing ship performance can be one of the feasible options to reduce emissions. However, simulating ship performance and precisely estimating its fuel consumption is challenging, as it demands the accurate representation of intricate features to mirror the actual navigation conditions. Therefore, developing a multi-objective AI-based digital twin can be an alternative to holistically capturing complex scenarios, ensuring the modeled scenarios are as realistic as possible.
- **Safety and Efficiency:** Ensuring the safety of maritime operations is paramount. However, the balance between safety and fuel consumption matters as well. If a ship focuses on minimizing fuel consumption solely without adequately considering ship stability and safety under different weather conditions and sea states, it would be risky for the ship when she navigates under unexpected weather conditions. Therefore, developing a model that can accurately estimate real-time ship motions and fuel consumption simultaneously under different hydrometeorological conditions is promising.
- **Technological Advancements and Real-world Applicability:** The use of emerging techniques, such as digital twins and deep learning models, in the maritime industry is becoming popular. Unlike the existing fuel consumption/ship motions prediction studies, except for the high prediction accuracy of the proposed model, this report attempts to deliver a solution for ships on real-time awareness of the optimal ship maneuvering command under distinct operational conditions by implementing the multi-objective AI-based digital twin.

This report makes the first attempt to integrate two different deep models into a ship digital twin to monitor and enhance the safety and efficiency of ship operations. To establish the digital twin, a massive amount of high-frequency sea trial data streams representing external conditions are invaluable. Ship motion and fuel consumption are modeled as functions of complicated external conditions. The bi-directional LSTM network with attention mechanisms is used to estimate ship fuel consumption, and the transformer neural network works on ship motion predictions, aiding in safety by providing early insight into potentially risky situations. The proposed digital twin model accurately predicts fuel consumption with an average loss range from -0.51% to 5.56% and ship motion with a loss range from 1.7% to 3.2%. The unseen data is used to test the model's generalization capability. The results prove that integrated models predict ship motions and fuel consumption effectively. Based on AI techniques, the proposed digital twin provides high-level insights into real-time ship performance awareness under different navigation conditions. In the long term, this model is helpful for the development of an intelligent decision support system regarding safety and efficiency improvement.

3. Literature survey

In this report, ship operation refers to the reflection of ship motion and fuel consumption estimation in diverse conditions. Models that have been used for the analysis of ship motions and fuel consumption can be broadly classified into two categories, namely (a) physics-based models and (b) AI models¹³.

3.1. Fuel consumption estimation

(1) Physics-based models for ship consumption estimation

Physics-based models can estimate ship fuel consumption in ship efficiency based on critical assumptions that utilize the relationship between ship resistance and engine power^{14, 16}. The estimation of fuel consumption is achieved via ship-propeller-engine performance models¹⁵. To accurately assess the total resistance experienced by a ship, both calm water resistance and added resistance are considered^{16, 17}. The physics-based models entail accounting for various components, including frictional resistance, appendage resistance, the bare hull and bulbous bow wave resistance, and additional resistance arising from the immersed transom and model-ship correlation¹⁸. Physics-based models have often been employed to estimate ship resistance in still water. Empirical methods proposed by the International Towing Tank Conference (ITTC) have been widely utilized¹⁹. The Holtrop-Mennen model-based methods have also been used at the preliminary stage²⁰. In recent years, Computational Fluid Dynamics (CFD) has been used in the detailed design stage²¹. Empirical methods can be utilized to estimate the added wave resistance^{22, 23}. Semi-empirical models have been proposed to account for the effects of wave-induced added resistance and ship motions. These models are based on experimental data and incorporate empirical equations to estimate added resistance in waves^{24, 25} and added resistance attributed to ship motions^{26, 27}. Consequently, ship propulsion systems are often analyzed using ship-propeller-engine performance models or simplified models based on the law of resistance transfer²⁸. However, accuracy may be limited when dealing with complex operational conditions²⁹. Additionally, these models often underestimate the interactions between ship systems in actual operational conditions, and therefore, their applicability is limited by simplified assumptions³⁰.

(2) AI models for ship consumption estimation

Artificial Intelligence methods offer a potential solution to overcome the challenges associated with physics-based models by leveraging big data to elucidate the intricate relationship between measured ship fuel consumption and a multitude of influential parameters (e.g., ship mechanical data and dynamics, main engine characteristics, weather conditions, and other relevant factors) ³¹. Review papers that discussed the potential application of AI methods (machine learning and deep learning methods) in predicting ship fuel consumption ^{29, 30}, identify three main clusters of commonly utilized methods, namely : (i) supervised machine learning methods ³², (ii) unsupervised machine learning methods ³³, and (iii) deep learning methods ³⁴. These methods may utilize diverse data sources and their combinations, such as voyage reports, Automatic Identification System (AIS), meteorological, and sensor data ³⁵. Various data sources enable accurate predictions. These algorithms can predict ship fuel consumption based on well-defined scenarios for a specific ship. However, they often struggle to accurately predict real-time ship fuel consumption for an entire ship voyage under complex operational conditions. This is because traditional machine learning/deep learning methods may not effectively deal with complex influencing factors and make informed predictions of ship fuel consumption.

3.2. Ship motion prediction

(1) Physics-based models for ship motion prediction

Over the years, physics-based methods have been used to describe ship motion dynamics and their consequences based on classic ship theory. Examples include the Abkowitz ³⁶, and the Manoeuvring Modeling Group (MMG) models ³⁷. Reduced order 4-DoF models or more detailed 6-DoF models have been developed to idealize the influence of nonlinear seakeeping and maneuvering characteristics on ship directional control ^{38, 39}. Kinematic models have also been introduced to better manage operational uncertainties and reduce computational costs. Recently, examples of rapid methods for analyzing ship evasiveness during critical events have been proposed by e.g., Taimuri et al. (2020) ⁴⁰; Gil et al. (2020) ⁴¹ and Gil. (2021) ⁴². In these methods, the hull-propeller-rudder interaction coefficients and hydrodynamic derivatives are used as critical parameters that represent original ship features. Standard parameter determination tools include the empirical method by Xu et al. (2022) ⁴³, the captive model test method of Okuda et al. (2022) ⁴⁴, Computational Fluid Dynamics (CFD) modeling methods such as the one by Lu et al. (2022) ⁴⁵, as well as system identification approaches, e.g., Ramirez et al. (2018) ⁴⁶. Their application is extremely useful for ship maneuvering simulations at the ship design stage. However, they fail to present a unified and convincing prediction of ship motions under environmental conditions in real time.

(2) AI models for ship motion prediction

A digital twin may be utilized to closely monitor seakeeping and maneuvering, especially during challenging operational conditions ^{5, 47, 48}. For example, research in big data science has the potential to predict hydrodynamic derivatives by utilizing results from model tests or open sea-trial data. To date, parametric estimation methods have been employed to quantify ship motions, relying on available ship mathematical models to train large data streams. For example, Wang et al. (2019) utilized the nu-support vector machine to identify hydrodynamic derivatives of the 3-DoF Abkowitz model ⁴⁹. Zeng et al. (2021) employed the Extended Kalman Filter (EKF) method to determine the hydrodynamic derivatives of an MMG model ⁵⁰. Non-parametric estimation models, such as Artificial Neural Networks (ANN) ⁵¹, Long Short-Term Memory (LSTM) ⁵⁴, Gaussian process regression ⁵², and locally weighted learning methods ⁵³, utilize simulated free-running tests to predict ship motion dynamics. Notably, Lou et al. (2020) ⁵⁵ developed neural network models to predict the motions of unmanned surface vehicles based on results from open seas maneuverability tests in 3-DoF. However, they often struggle to predict real-time ship motions in complex operational conditions accurately. This is because traditional machine learning/deep learning methods may not effectively identify and capture ship maneuvering systems to predict ship motions reflecting hydrometeorological conditions.

The critical review of methods for the ship digital twins in ship operations indicates that existing digital twin models have limitations. A common challenge is the accuracy of the digital twin representation. While digital twins aim to replicate physical objects or systems, there may still be discrepancies due to limitations in data collection, model accuracy, or real-time updates. For example, accuracy in terms of visualization can be compromised because of the limited ability of parametric or non-parametric statistical regression models to consider medium to long-term environmental conditions. A high-fidelity digital twin requires careful calibration, validation, and continuous improvement to ensure reliability and accuracy.

Based on the critical literature, the existing research in the field of ship motion prediction and fuel consumption estimation, particularly concerning the use of digital twin models, has identified several critical gaps:

- **Limited Accuracy of Digital Twins:** While digital twins aim to replicate physical ship operations, there are inherent limitations in terms of accuracy. Discrepancies arise due to constraints in data collection, model accuracy, and real-time updates. For example, existing models may struggle to consider medium to long-term environmental conditions, which are crucial for predicting ship behavior accurately.
- **Challenges in Complex Operational Conditions:** Current models often struggle to accurately predict real-time ship motions and fuel consumption under complex operational conditions. As shown in Figure 2, the intricate interplay between ship dynamics, systems, and navigation patterns is often underestimated.
- **Need for Real-Time Monitoring:** Digital twins should ideally provide real-time monitoring of ship operations, especially during challenging conditions. However, achieving this in practice remains a significant challenge, and there is room for improving the timeliness and responsiveness of digital twin models.
- **Time-Consuming Calculations and Absence of Optimization Iteration:** Many digital twin models involve complex computations that consume substantial resources and time to generate accurate predictions. Additionally, these models often lack the capability for iterative optimization. In dynamic real-world conditions, such as changing weather, traffic, or cargo load, ships' movements and fuel consumption are affected. Without the ability to continuously refine predictions based on real-time data, these models may struggle to adapt effectively, potentially leading to suboptimal operational decisions. Therefore, there is a pressing need for more efficient computational algorithms and iterative processes to enhance the accuracy and responsiveness of digital twin models for ship operations by adapting to evolving conditions.

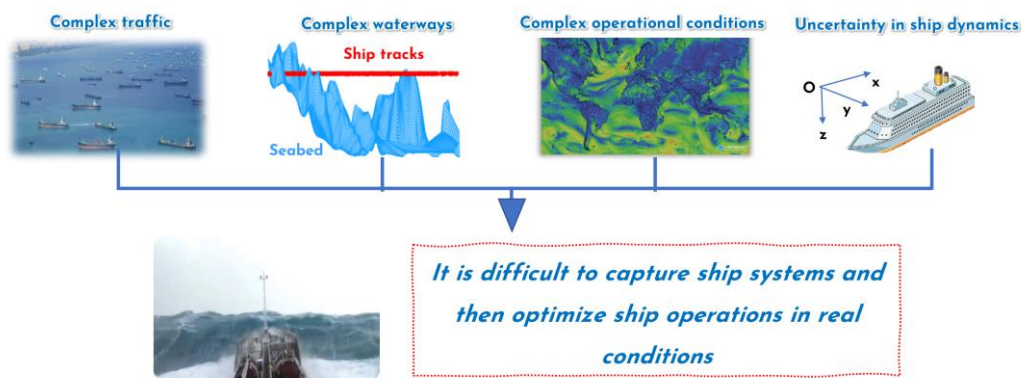


Figure 2. The complexities of ship operations in actual conditions.

4. Proposed solution

To bridge the research gaps and advance the field of safety and sustainability improvement of ship operations using AI techniques, the following strategies and approaches are considered:

- **Advanced Machine Learning Techniques:** Explore advanced machine learning and deep learning techniques, such as generative adversarial networks or hybrid models, which can better capture the complexity of ship operations. These techniques can be applied to enhance the accuracy of ship motions and fuel consumption predictions under complex operational conditions.
- **Data Fusion and Integration:** Investigate strategies for fusing and integrating data from various sources, including voyage reports, model tests, and open sea-trial data. Creating a comprehensive and well-structured dataset is crucial for training an accurate digital twin model. In addition, research is expected to focus on developing models that can account for medium to long-term environmental conditions. Historical data and scenario-based forecasting ability are necessary to achieve a digital twin capable of representing a physical model over an extended timeframe.
- **Incorporate Real-Time Data:** Develop methods for incorporating real-time data from diverse sources, such as sensors, meteorological data, and Automatic Identification System (AIS) data, into digital twin models. This will enable more accurate real-time monitoring of ship operations and better predict ship behaviors.
- **Rapid optimization:** AI techniques have the potential to play a crucial role in enhancing digital twin models for ship operations by addressing the challenges of time-consuming calculations and the absence of optimization iteration. Their efficiency in learning complex patterns, real-time adaptability, and iterative optimization capabilities make them well-suited to handle ship operations' dynamic and data-intensive nature. Their feature extraction, scalability, and generalization capabilities make them versatile tools for predicting ship operations in various conditions. Importantly, AI models can continuously improve as they can handle a massive amount of data, making them valuable for enhancing the accuracy and responsiveness of digital twin models in real-world, evolving scenarios.

Accordingly, this report discusses the potential of an AI-based digital twin model to monitor and estimate ship safety and efficiency. The primary aim is to provide insights into the awareness improvement for the ship best navigational performance, proactively improving safety and sustainability of ship operations. A digital twin introduced in this report encompasses two sub models with different purposes in ensuring ship safety and monitoring fuel consumption. Figure 3 represents the architecture of the digital twin models, illustrating the integration of sub-model 1, bi-directional Long Short-Term Memory (Bi-LSTM) with an attention mechanism for the prediction of ship efficiency, and sub model 2, a transformer model for the identification of ship motions. The detailed information is described in Sections 5, along with thorough validation and generalization capability test results.

- **Sub model 1** focuses on idealizing the ship's energy systems and predicting fuel consumption¹². This sub model can accurately estimate the ship's fuel consumption in various operating scenarios. It considers ship operational characteristics (ship speed, draft, trim, etc.) and the influence of environmental conditions (wind, wave, and current, etc.). Predictive analytics is crucial for ship operators who seek to optimize fuel usage, reduce costs, and decarbonize fleet operations.
- **Sub model 2** is used to understand and predict ship motions in realistic, complex hydrometeorological conditions⁹. Ship motions influence ship stability, safety, and cargo integrity. Hence, this sub model is trained by collected datasets capturing the complex relationships among various ship systems and operational factors (e.g., rudder angle, propeller rpm, speed, heading, weather condition) that impact ship motions in 6 Degrees of Freedom (DoF) and real-time. In this case, predictive analytics enables ship operators to proactively respond to potentially hazardous conditions (e.g., ship–ship collision and ship grounding), adjust navigation strategies, and ensure ship safety.

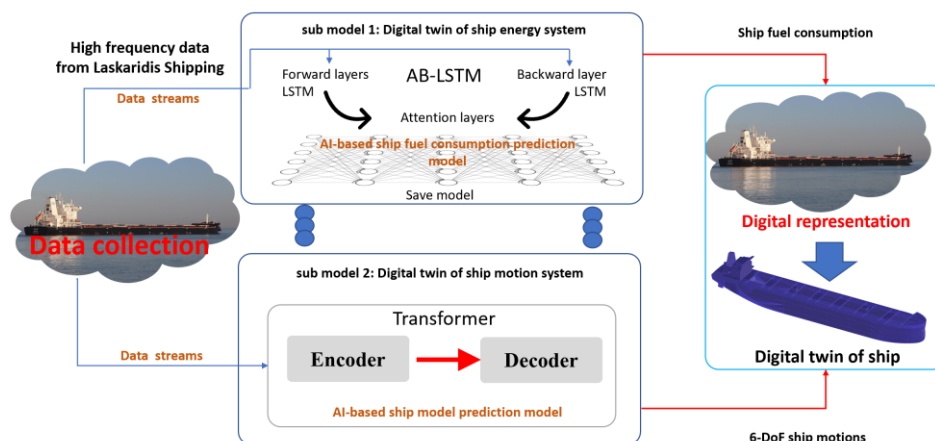
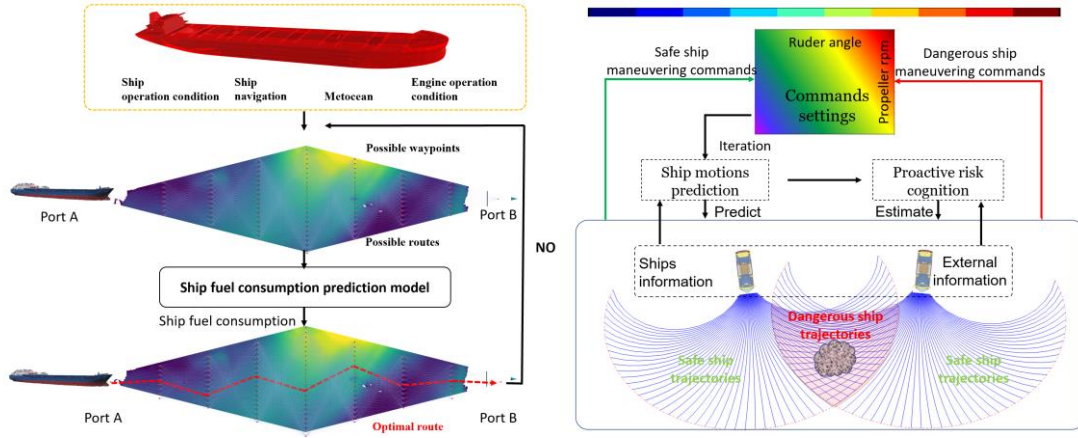


Figure 3. The overall procedure of AI-based ship digital twin.

Once the digital twin is successfully established, it is anticipated to be utilized for the corresponding ship, providing insights into the optimal ship maneuvering commands across diverse scenarios. The aim is to empower the digital twin to conduct simulations across all viable navigational paths, taking into account the associated operational conditions, such as the ship status and the external factors (i.e., wind, wave, current, and water depths) from the start to the end of the voyage. Each viable path represents a possibility, and for every path, the digital twin generates time-sequential series of predictive values for the ship motion and fuel consumption, with the model continuously iterating and updating the predictions based on the unfolding time. The digital twin systematically goes through all possible options, calculating the safe ship movements and the associated fuel consumption at each moment of the voyage. As depicted in Figure 4, the ship operators can be able to discern the most advantageous navigational command from among all the viable alternatives. For example, when the digital twin initiates the voyage simulation, for every voyage, the digital twin can estimate the real-time fuel consumption (as shown in Figure 4(a)). At the same time, under the same scenario, 6 DoF ship motions can be predicted as well. Figure 4 (b) shows that some operational conditions may lead to proactive risk cognitions, such as shallow water or obstacles. Under a state of adverse consequences (i.e., collision or grounding), ship motions command garners the label of "dangerous." Conversely, if undesired outcomes are

absent, the maneuvering command attains the label of "safe." Such a system can be employed to support safe and sustainable decision-making.



(a). Sub model 1 for fuel consumption prediction (b). Sub model 1 for ship motion prediction
Figure 4. Multi-objective optimization method for sustainable ship operations based on prediction model.

5. Detailed design description

5.1. Methods description

5.1.1 Sub model 1: A digital twin for fuel efficiency estimation

This section introduces the deep learning model based on Bi-LSTM with attention mechanisms¹². The architecture of the system, as illustrated in Figure 5, comprises four main components, namely: (i) input layers, (ii) Bi-LSTM layers, (iii) attention layers, and (iv) the output layer.

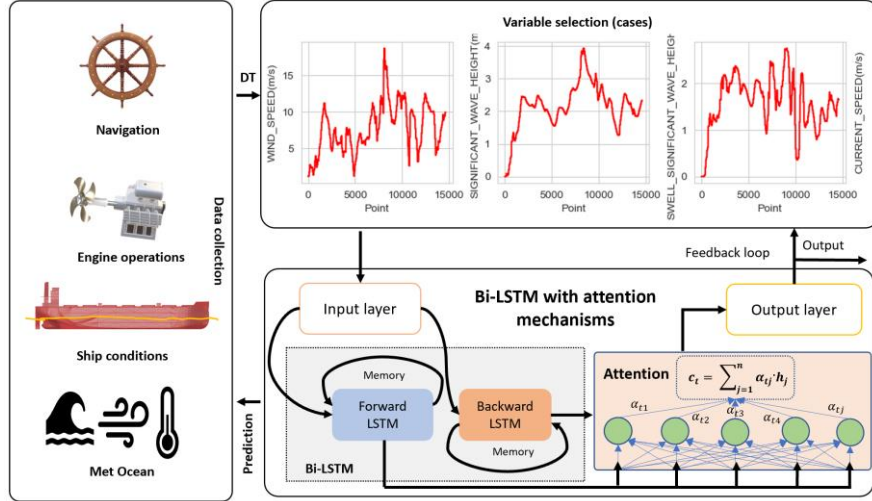


Figure 5. The schematic of the AI-based digital twin of the ship energy system.

The model combines the strengths of Bi-LSTM, which can capture both past and future dependencies, with attention mechanisms that enable the model to focus on relevant parts of the input data streams. Table 1 summarizes the algorithm, outlining the step-by-step procedure, including data pre-processing, model architecture setup, training process, and prediction generation. The layers of the sub model 1 are summarized as follows:

(1) Input layers

The **input layers** accept key variables obtained from navigation data, engine operation data, ship condition data, and hydrometeorological conditions from sea trials. Then, these selected variables are pre-processed and fed into the subsequent layers.

Table 1. Algorithm 1- Bi-LSTM with attention mechanism for ship fuel consumption prediction.

Algorithm: Bi-LSTM with attention mechanisms for ship fuel consumption (SFC) prediction	
1	Input: Data collection SFC(n), see more in Section 2.1
2	Output: AI-based ship fuel consumption surrogate model
3	Select key variables X(n) and ship fuel consumption SFC (n) in the time domain.
4	split the training data set $data_{train}$ and $data_{test}$ from X(n) using k folds cross-validation method.
5	For batch $data_{batchsize}$ in $data_{train}$
6	For L-length data $data_l$ in $data_{batchsize}$
7	For $i = 1$ to L
8	Using forward LSTM to an encoder, $\overrightarrow{h_t}$
9	Using backward LSTM to an encoder, $\overleftarrow{h_t}$
10	End For
11	Compute Attention score α_i and c_t
12	Compute ship fuel consumption SFC_t from c_t
13	End For
14	Training the model to identify ship energy system in actual operational conditions
15	End For
16	Save the prediction model: AI-based ship fuel consumption prediction model

(2) Bi-LSTM layer

Each **Bi-LSTM layer** consists of two LSTM sublayers. Each LSTM unit comprises four interconnected elements, including the input and control signals for the input, forgotten, and output gates ⁵⁶. These components work together to regulate memory storage, retention, and output. Figure 6 depicts the internal structure of the LSTM unit (see red box). The input x_t at a time increment t and the output h_{t-1} of the hidden layer neuron at a time increment $t-1$ represent the joint inputs to the hidden layer. These inputs are then multiplied by distinct weight vectors, and upon application of the activation function, the control signals f_t , i_t , o_t , of the forgotten gate, input gate, and output gate are generated. This process is represented by Eqs. (1-3), where the weight vector is denoted by w and the activation amount by b . The biases for different connection weights are represented by b_f , b_i , and b_o , and $\sigma(\cdot)$ is the sigmoid activation function.

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (3)$$

The state of a cell $\tilde{C}_t$ is presented as per Eq. (4). The value of the memory unit C_t is updated as per Eq. (5). Accordingly, the output of hidden layer neurons h_t can be presented as per Eq. (6)

$$\tilde{C}_t = \tanh(w_c[h_{t-1}, x_t] + b_c) \quad (4)$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad (5)$$

$$h_t = o_t \tanh(C_t) \quad (6)$$

where $\tanh(\cdot)$ represents a hyperbolic tangent activation function.

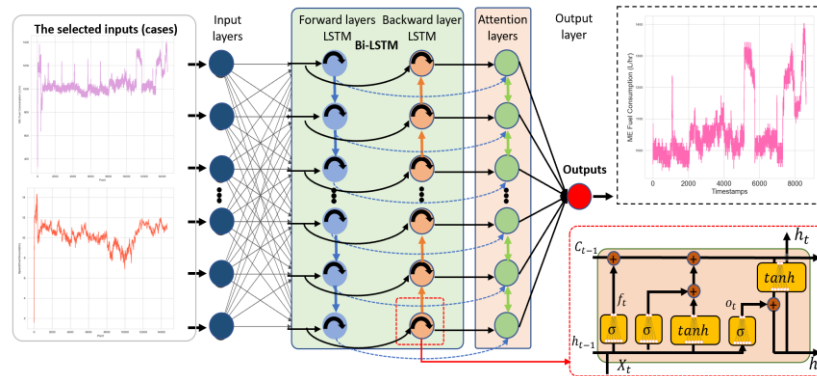


Figure 6. The architecture of Bi-LSTM with attention mechanisms.

Ships are systems of systems that navigate through complex operational conditions ⁵⁷. To effectively capture the complexity of ship systems using actual operational data for ship fuel consumption prediction, it is essential for the model to learn from both past and future information in the data streams. While a standard LSTM model only considers information from past time frames in the data stream, the bi-LSTM layer overcomes this limitation by addressing the problem of disregarding relevant past information ⁵⁸. This is because it comprises both forward and backward LSTM sublayers, see Figure 7. Forward sublayers process the input stream in a forward direction, i.e., from the beginning t_b to the end t_e . In a backward direction the sublayers operate from the end t_e to the beginning t_b , see more in Figure 7.

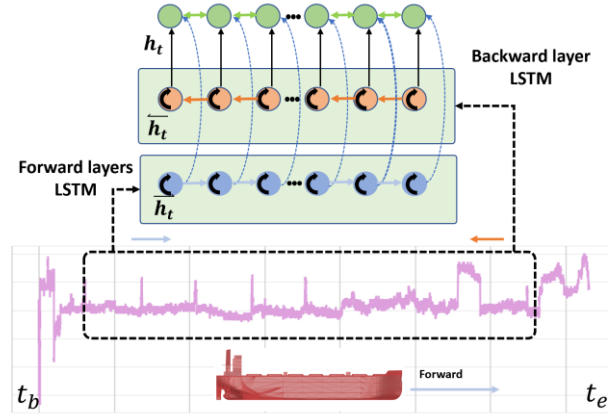


Figure 7. Capturing and utilizing information from both forward and backward directions.

A bidirectional LSTM processes input data stream in both forward and backward directions. By concatenating the outputs of the forward and backward LSTMs, the model could obtain a representation that incorporates both past and future information, as shown in Figure 7. Given an input data stream $X = [x_1, x_2, \dots, x_n]$, a bidirectional LSTM generates hidden states in both forward and backward directions as shown in Eqs. (7-8). The hidden states from both directions are concatenated to obtain a comprehensive representation at each time step as Eq. (9).

$$\vec{h}_t = \text{LSTM}(x_t, \vec{h}_{t-1}) \quad (7)$$

$$\overleftarrow{h}_t = \text{LSTM}(x_t, \overleftarrow{h}_{t+1}) \quad (8)$$

$$h_t = [\vec{h}_t, \overleftarrow{h}_t] \quad (9)$$

where t represents the time step, and $\vec{h}_t$ is the hidden state in the forward direction. $\overleftarrow{h}_t$ is the hidden state in the backward direction, $[\cdot]$ denotes the concatenation.

(3) Attention mechanism layer

The **attention mechanism** allows the model to dynamically focus on different parts of the input data streams, thus assigning varying levels of importance to different time steps ⁹. This enhances the ability to emphasize critical information from data streams, which is useful to capture extreme scenarios of ship operations in actual complex operational conditions. The attention layers calculate attention scores and weights for each time step based on the hidden representations from the Bi-LSTM layers, as shown in Figure 8.

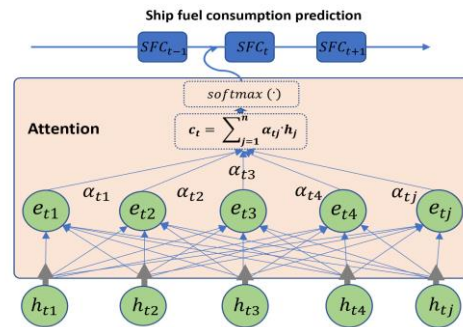


Figure 8. Attention mechanism for the prediction of ship fuel consumption.

Given a specific time step t , the attention weight α_{tj} of other hidden layers for the current input for x_t is calculated as Eq. (10). The alignment score e_{tj} computed using a trainable alignment model is defined as Eq. (11). The context vector c_t is the weighted sum of the hidden states, which reflects the attended information at

time step t as Eq. (12). The final output SFC_t at time step t is generated by passing the context vector c_t through a linear transformation and an activation function as Eq. (13).

$$\alpha_{tj} = \frac{\exp(e_{tj})}{\sum_{j=1}^n \exp(e_{tj})} \quad (10)$$

$$e_{tj} = \text{align}(h_t, h_j) \quad (11)$$

$$c_t = \sum_{j=1}^n \alpha_{tj} \cdot h_j \quad (12)$$

$$SFC_t = \text{softmax}(W_c \cdot c_t + b_c) \quad (13)$$

where W_c , and b_c are parameters (weight matrices or vectors) that are typically trained and determined during the process of model training.

(4) Output layer

The **output layer** receives the context vector, the weighted combination of the hidden representations obtained from the attention layers. The context vector captures the most relevant information from the input data stream. The output layer processes the context vectors and predicts the ship fuel consumption for the given time step, see Figure 8.

5.1.2. Sub model 2: A digital twin for ship motion prediction

The transformer is an advanced deep learning architecture that utilizes self- and multi-head attention mechanisms⁹. It enables the differential weighting of input features to determine their importance. This section introduces a transformer-based digital twin of the ship motion system. A transformer-based deep learning method is employed to train ship trajectory data streams and make long-term ship motion predictions in the time domain. Figure 9 illustrates a ship trajectory with time series of ship motions influenced by environmental conditions that are used to train the model. Each point on the trajectory includes ship control actions, desired inputs, environmental conditions, and 6-DoF ship motions. The model can identify and forecast 6-DoF ship motions. The transformer architecture, illustrated in Figure 10, consists of encoder and decoder modules, each containing multiple blocks represented by grey areas⁵⁹.

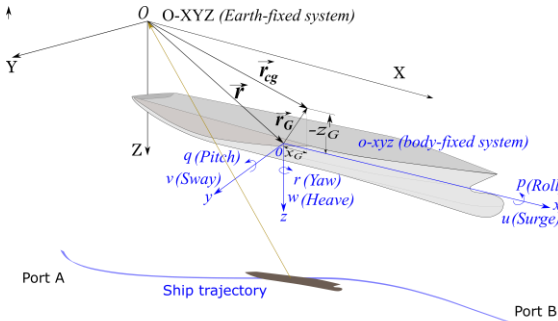


Figure 9. 6-DoF ship motion dynamics.

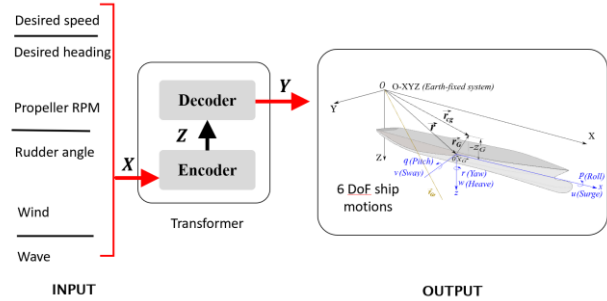


Figure 10. Transformer for ship motion prediction.

Encoder module incorporates multi-head attention and a feed-forward neural network, enabling the mapping of time series data related to operational conditions, control devices, and desired inputs (see X in Eq. (14)) to a new continuous series (Z in Eq. (15)). This mapping is achieved via an "attention mechanism" defined by the SoftMax function in Eq. (19). The objective is to predict the time series of ship motions (Y in Eq. (16)) using an autoregressive method. The attention mechanism employed in the digital twin model facilitates the retention of crucial information during the training and prediction of significant data streams⁶⁰.

$$X = \{x_1, x_2, x_3, \dots, x_n\} \quad (14)$$

$$Z = \{z_1, z_2, z_3, \dots, z_n\} \quad (15)$$

$$Y = \{y_1, y_2, y_3, \dots, y_n\} \quad (16)$$

Where X denotes the matrix of control devices, conditions, and desired inputs in the time domain; Y denotes the matrix of the 6-DoF ship motion in the time domain; Z denotes a matrix after encoding; x_n denotes the inputs of control devices, conditions, and desired inputs at point n ; y_n denotes the outputs of 6-DoF at point n .

Figure 11 presents a deep learning network consisting of an encoder and decoder, both composed of multiple layers of attention. The network aims to process and analyze training data streams of ship motions. Initially, the

ship motion data is fed into an “Input Embedding layer” which treats the data as a lookup table to generate a learned vector representation of ship motions. A feed-forward neural network layer then learns the number of lookup tables from the training database, allowing the ship motion data streams from different ship trajectories to be organized into vectors. To account for variations over sea depth and across a trajectory, a smart positional encoding scheme is employed to incorporate positional information of data streams into the vectors from the Input Embedding layer^{59,60}.

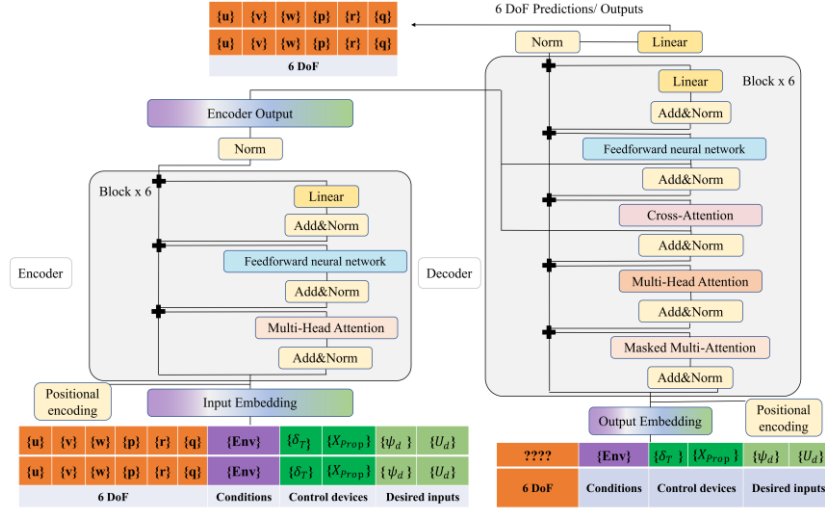


Figure 11. Transformer architecture for 6-DoF ship motion prediction.

This encoding process is defined mathematically by Eqs. (17)-(18)⁶¹. The input vectors, resulting from the embedding and positional encoding of ship motion data, are combined and used to train the encoder and decoder modules of model⁹.

$$PE_{(pos,2i)} = \sin(pos/10000^{2i/d_{model}}) \quad (17)$$

$$PE_{(pos,2i+1)} = \cos(pos/10000^{2i/d_{model}}) \quad (18)$$

where, pos denotes the location of the time series of ship motions, and i presents the dimensionality of d_{model} .

Once the vector with positional encoding is passed to the encoder and decoder modules (Figure 11), the encoder module maps the input time series to a set of new continuous series. The decoder module utilizes an auto-regressive technique to generate the output time series for ship motion prediction, see Eqs. (14)-(16). Both the encoder and decoder consist of similar sub-layers. The encoder and decoder modules encompass the following components: (1) Attention mechanism/multi-head attention/marked multi-head attention layer; (2) Add & Norm function layer; (3) Feed-forward networks (FFN) layer; and (4) Linear layer⁹.

(1) Attention mechanism / multi-head attention layer

The attention mechanism in the deep learning model provides exceptional long-term memory for ship motion time series, allowing the model to attend to and focus on the ship motion information during the entire voyage. The attention layer and SoftMax functions are defined based on Eq. (19) in the transformer architecture, as described in Vaswani et al. (2017)⁶¹.

$$z = \text{Attention}(Q, K, V) = \text{SoftMax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (19)$$

where Q , K , and V are query, key, and information value vectors, $Q \in R^{n \times d_k}$, $K \in R^{m \times d_k}$, $V \in R^{m \times d_v}$ are the matrixes, including query, key, and value of attention; d_k denotes the dimensions in blocks. $Q = X \times QW$, $K = X \times KW$, $V = X \times VW$. QW , KW , and VW are weight matrixes; z denotes an element of the matrix Z which is calculated using SoftMax functions.

Each attention process in this model functions as a learning mechanism for ship motions. Multiple attention heads can predict output vectors, which are then concatenated into a single output vector. This multi-head attention approach enables the learning of more comprehensive information about ship motions compared to a single attention layer. The multi-head attention layer consists of individual attention layers as denoted in Eqs. (20)-(21). The marked multi-head attention layer represents a hidden layer within the multi-head attention. The

use of a mask indicates a matrix that scales the attention scores of the multi-head attention layer, as further detailed in Bhattacharya et al. (2022) ⁶².

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \quad (20)$$

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (21)$$

where, $W^O \in R^{h \times d_{\text{model}} \times d_k}$, h denotes the number of parallel attention layers. QW, KW , and VW are weight matrices, $W_i^Q \in R^{d_{\text{model}} \times d_k}$, $W_i^K \in R^{d_{\text{model}} \times d_k}$, $W_i^V \in R^{d_{\text{model}} \times d_k}$.

(2) Add & Norm layers

To incorporate the output vector from the hidden multi-head attention layer with the original positional input embedding of the ship's time domain motion, Add & Norm layers are utilized. The Add layer consists of a residual network or residual connection, which enables the learning of residual functions for the inputs, as shown in Eq. (22). The output of the Add layer then passes through a Norm layer, which applies layer normalization to enhance performance and training efficiency, as described in Eqs. (22)-(25). These layers facilitate the integration and normalization of the input and output vectors in the model.

$$F(x) = H(x) - x \quad (22)$$

$$\mu^l = \frac{1}{h} \sum_{i=1}^h a_i^l \quad (23)$$

$$\sigma^l = \sqrt{\frac{1}{h} \sum_{i=1}^h (a_i^l - \sigma_\mu^l)^2} \quad (24)$$

$$\hat{a}^l = \frac{a^l - \sigma_\mu^l}{\sqrt{(\sigma^l)^2 + \varepsilon}} \quad (25)$$

where, $H(x)$ is the desired mapping, $F(x)$ denotes the stacked nonlinear layers, and the original mapping reconstructed as $F(x) + x$; h denotes the number of nodes of the hidden layer; l denotes the number of layers. The σ^l and μ^l are the parameters of layer normalization; σ_μ^l is the mean value; $\hat{a}^l$ denotes the results of layer normalization and ε denotes a very small number that can be used to avoid $\sqrt{(\sigma^l)^2 + \varepsilon} = 0$, see Eq. (25).

(3) Feed-forward network

The output from the Add & Norm layers is then passed through feed-forward networks for additional processing. The Feed-Forward Network (FFN) is employed to enhance network stability and reduce training time. It consists of multiple linear layers, with a Rectified Linear Units (ReLU) activation function, connecting each sub-layer. Further details can be found in the work by Li et al. (2019) ⁶³.

$$\text{FFN}(x) = \max(0, xW_1 + b_1) W_2 + b_2 \quad (26)$$

$$\text{ReLU}(x) = (x)^+ = \max(0, x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases} \quad (27)$$

where, the function $\max()$ denotes the ReLU function as per Eq. (27); W_1 , and W_2 represent the value of slope; b_1 , and b_2 represent the value of intercept.

(4) Linear layer

The decoder is capped off with a linear layer that acts as a classifier to present the predicted outputs. The linear function is the linear transformation of data streams ⁶¹

$$y = xA^T + b \quad (28)$$

where, A^T represents the value of slope; b represents the value of intercept.

The complex architecture of the transformer allows learning different ship motion dynamics in real conditions, potentially boosting the predictive ability of the ship maneuvering features of the selected ship, see testing and validation in Section 5.2. To evaluate the performance and quantify the errors between the real and digital twin, Root Mean Square Error (RMSE), Mean Square Error (RMSE), and error rate e_n are used as shown in Eqs. (29-31).

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (y_n - \hat{y}_n)^2} \quad (29)$$

$$MSE = \frac{1}{N} \sum_{n=1}^N (y_n - \hat{y}_n)^2 \quad (30)$$

$$e_n = (y_n - \hat{y}_n) / (y_n) \quad (31)$$

where y_n is the actual value, $\hat{y}_n$ denotes the predicted value, $\bar{y}_n$ is the mean value.

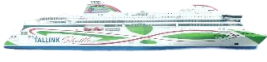
5.2. Results description

This section demonstrates the use of multi-objective AI-based digital twin models ^{9, 12}. Sub model 1 of the digital twin model was trained by utilizing extensive data streams derived from high-frequency sea trial data of a Kamsarmax bulk carrier owned by Laskaridis Shipping Co. Ltd. (see Table 2). Figure 12 illustrates voyages from sea trial data collected for this vessel from February 2021 to February 2023. Sub model 2 of the digital twin model was trained using operational data from the Ro-Pax ship owned by Viking Line Co. Ltd (see Table 3). Trajectories and hydro-meteorological conditions were observed between two ports in the Gulf of Finland, as shown in Figure 13 ⁹. This approach was adopted due to the inherent challenge of collecting all the required data from a single ship.

Table 2. Ship specification of the KAMSARMAX class bulk carrier.

Information			
IMO	9843405		
Vessel Type	Bulk Carrier		Real
DWT	81 600.0 t		Digital Twin
Length x Breadth	229.0 x 32.0 m		
Year Built	2020		

Table 3. The ship specification of the selected Ro-Pax ship.

Information			
IMO	9773064		
Vessel Type	Ro-Pax ship		Real
DWT	49 134.0 t		Digital Twin
Length x Breadth	212.0 x 30.6 m		
Year Built	2017		

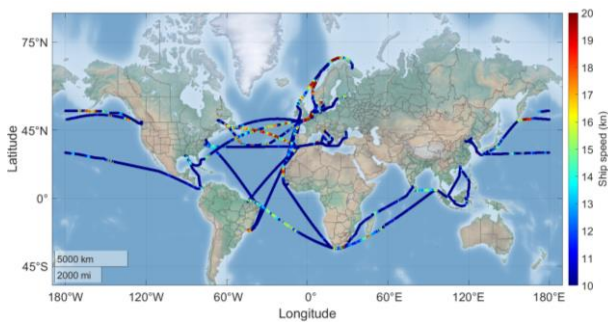


Figure 12. Sea trial data of the selected bulk carrier.

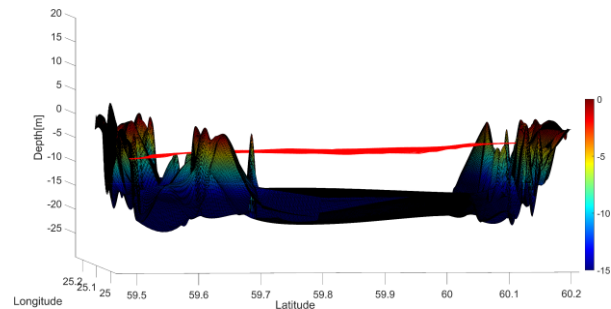


Figure 13. Ship voyages from Helsinki to Tallinn.

5.2.1. Ship fuel consumption predictive analytics

A Bi-LSTM architecture was employed to train a digital twin of the ship energy systems. Inputs to the model contains ship navigation data, such as ship speed, course and heading, operational conditions (e.g., ship mean draft and trim, main engine shaft power and temperature), and Metocean data encompassing wave characteristics, wind conditions, current information, and air temperature. These inputs were carefully selected based on their relevance to fuel consumption prediction. The output of the model is the ship fuel consumption represented in the time domain. This information was utilized to drive the predictions generated by the digital twin. A visual representation of the model architecture and its components can be found in

Figure 14. The model architecture consists of an input layer, three Bi-LSTM layers, three attention layers, and an output layer. The Bi-LSTM layer had 128 hidden units. The model characteristics and the selected hyperparameters are presented in Table 4.

Table 4. The model characteristics and the optimal hyperparameters.

Model	Input variables	output variable	layers
Bi-LSTM	14	1	7
Hidden units per layer	Optimizer	Batch Size	Early stopping
128	Adam	48	Patience=10
Dropout rate	Leaning rate	Epochs	Regularization param
0.2	5e-05	178	0.1

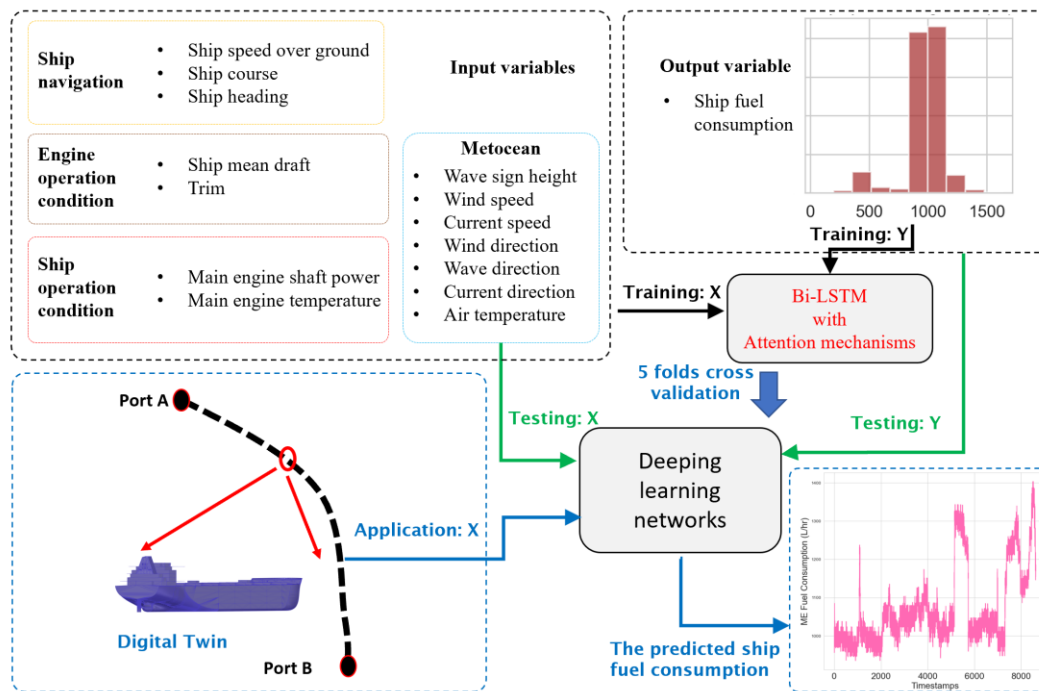


Figure 14. The digital twin processing of ship fuel consumption prediction for model training, testing, and application.

The training loss and validation loss were calculated using the training (80%) and validation (20%) datasets, respectively. The curves shown in Figure 15 show that both decreased and stabilized around the 178th epoch. Therefore, if no improvement in the validation performance is observed beyond this point, the training process is terminated early to prevent overfitting. After completing 178 epochs, the deep learning model achieved an optimal fitting state, indicating a balanced convergence between the model's performance and the training data. This optimal fitting state implies that the model does not suffer from overfitting, characterized by excessive complexity and high accuracy on the training data but poor generalization to testing data. It also avoids underfitting, which occurs when the model fails to capture underlying patterns in the data, resulting in subpar performance on both training and testing data.

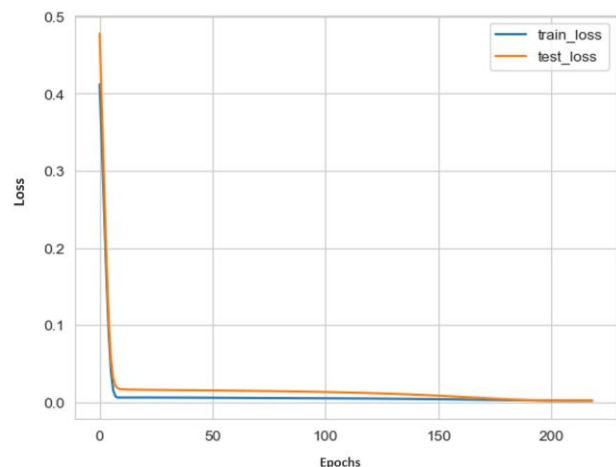


Figure 15. The model performance evaluation.

As depicted in Figure 15, the training process demonstrates that the deep learning model can achieve an optimal fit, effectively addressing both overfitting and underfitting. The average validation loss using Mean Squared Error (MSE) is determined to be $2.04e-2$. To further evaluate the trained deep learning model, new inputs were selected from the testing database. As shown in Figure 16, the model was used to predict ship fuel consumption in the time domain, and the resulting error rates were calculated using Eq. (31). The results of ship fuel consumption prediction are illustrated in the upper figure in Figure 16. The red line represents the real values of ship fuel consumption, while the green line represents the predicted results. The alignment and deviation between the two lines indicate the accuracy of the digital twin. In the bottom figure, the blue line represents the error rate in the time domain. It shows the magnitude and direction of the errors between the predicted and actual fuel consumption values at different points in time. These findings indicate that the trained deep learning model can effectively capture the characteristics of the ship energy system under real operational conditions. Further analysis of the prediction errors is presented in Figure 17. Over 90% of errors are below 4%, with an average error rate of 0.98%. It is important to note that the proposed model has limitations in effectively capturing abnormal fluctuations present in the sensor-collected data. This is also reflected in the significant errors indicated by the peak values in lower Figure 16. Thus, it is evident that the digital twin of the ship energy system built using the deep learning model achieves a desirable equilibrium by effectively capturing the intricacies of the training data while also generalizing well to new data streams.

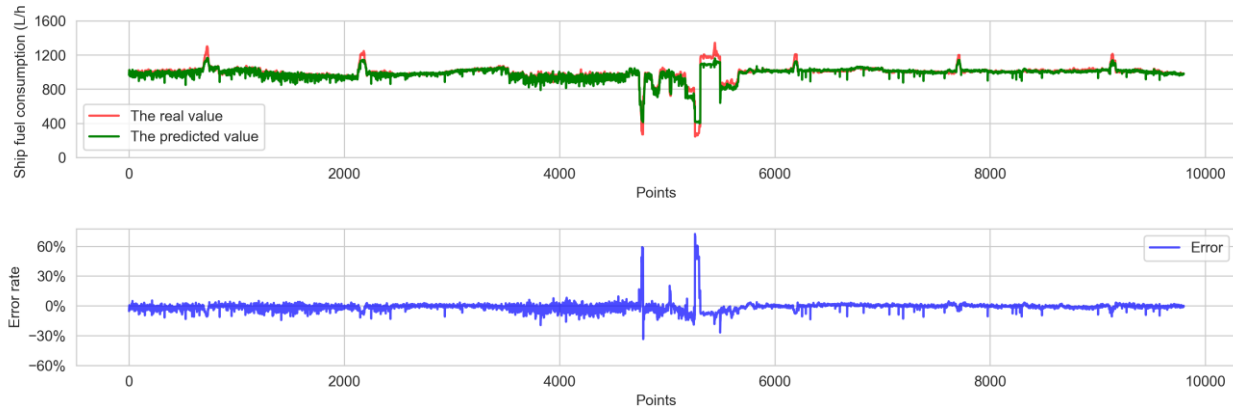


Figure 16. The comparison of real and predicted ship fuel consumption.

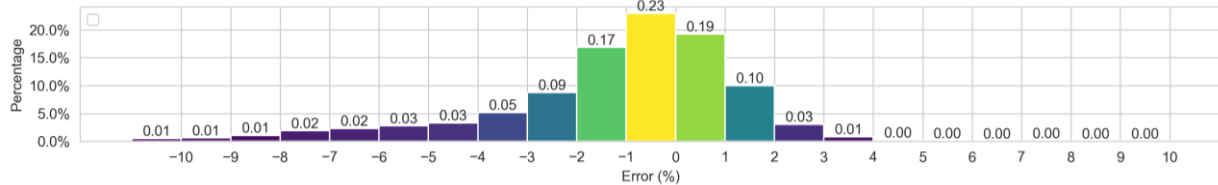


Figure 17. The analysis of prediction errors using the proposed model.

5.2.2. Ship motions predictive analytics

For the typical Ro-Pax ship shown in Table 3, ship trajectories were collected during the ice-free period between 2018 and 2019. The waterway between Helsinki and Tallinn may freeze during the winter months of December, January, and February. However, this aspect is not considered in the present analysis.

A 6-DoF ship dynamics model⁶⁴ was utilized to generate time-domain input parameters (rudder angle, propeller rpm) and time-domain output results (6-DoF ship motion dynamics) for 500 voyages between Helsinki and Tallinn. Subsequently, a transformer architecture was developed to train a deep-learning model that maps the inputs to the outputs. Inputs $\{X\}$ encompass rudder angle, propeller rpm, speed, heading, wind information, and wave information. Outputs $\{Y\}$ comprise surge, sway, heave, roll, pitch, and yaw. This information was employed to guide the predictions produced by the digital twin of the ship motion system. A visual representation of the model architecture and its components can be found in Figure 18. A complex architecture of the transformer was designed to capture the key features of historical ship motion dynamics. Model characteristics and selected hyperparameters are presented in Table 5.

The total dataset comprised a total of 500 voyages divided into three parts: 80% for training (400 ship voyages), 10% for validation (50 voyages), and 10% (50 voyages) for testing. The curves shown in Figure 19 demonstrate that both the training and validation losses decrease and stabilize at the 38th epoch. The results of the training

process indicate that the deep learning model achieves an optimal fit, indicating that it neither overfits nor underfits the data. To test the digital twin of the ship motion system, the future inputs of ship control actions, desired inputs, and environmental conditions were considered. The 6-DoF ship motions were then predicted, as depicted in Figure 20. The ground truth represents the real data in blue. The prediction denotes the predicted results in red. These results demonstrate that the digital twin model can effectively capture the ship motion features in real-world conditions.

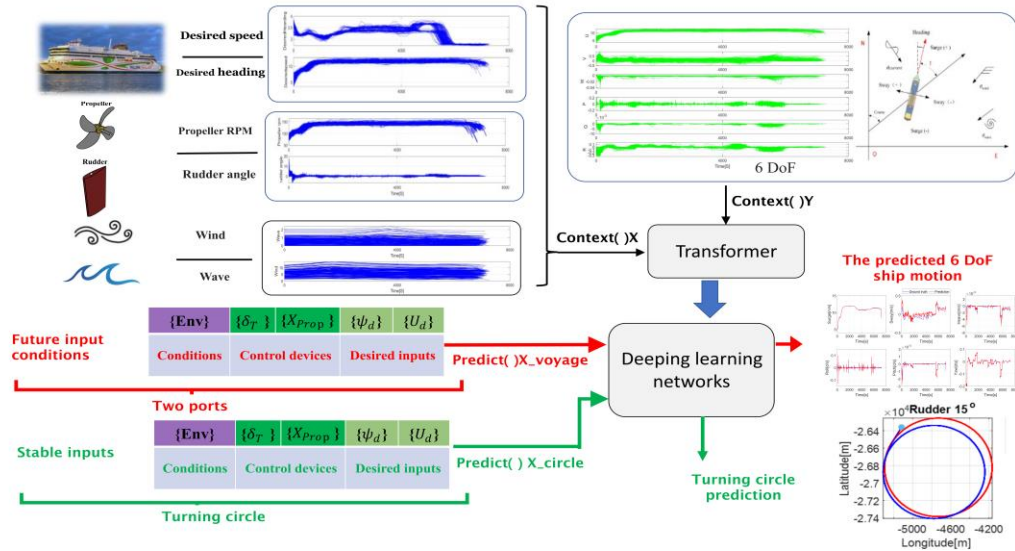


Figure 18. The digital twin processing of 6-DoF ship motion prediction for the long-term voyage in real conditions and turning circle in calm conditions.

Table 5. The model characteristics and hyperparameters of the transformer.

Model	Input variables	Output variable	Encoder
Transformer	8	6	6 blocks
Decoder	Optimizer	Batch Size	Dimension
6 blocks	Adam	8	256
Encoder	Encoder module	Inner layers	Epochs
1 parallel attention layer	3 parallel attention layers	1,024 dimensions	48

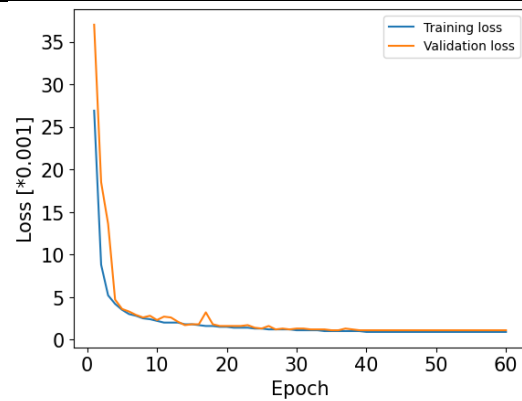


Figure 19. The model performance evaluation.

To accurately evaluate the performance of the trained model, R^2 values were calculated and assessed (Figure 21). The R^2 values for surge, roll, and pitch predictions exceeded 0.9, thus indicating a strong correlation between the predicted and real values. The R^2 values for sway and heave predictions are 0.62 and 0.65, respectively. These results suggest that the predicted and real values are in close agreement. The model demonstrated good performance in predicting all 6-DoF ship motions. However, the agreement for sway and heave predictions is slightly lower compared to surge, roll, and pitch. This discrepancy may be attributed to the adopted method, which is based on an auto-regression model that may underestimate certain influential factors in ship sway and heave, such as swell and current.

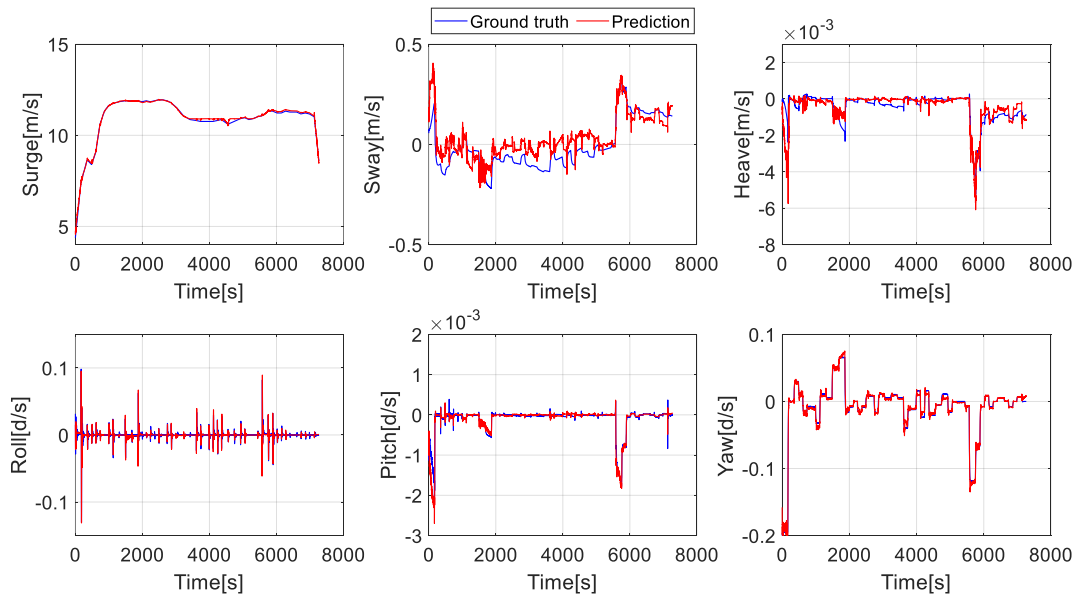


Figure 20. The comparison of real and predicted ship motions.

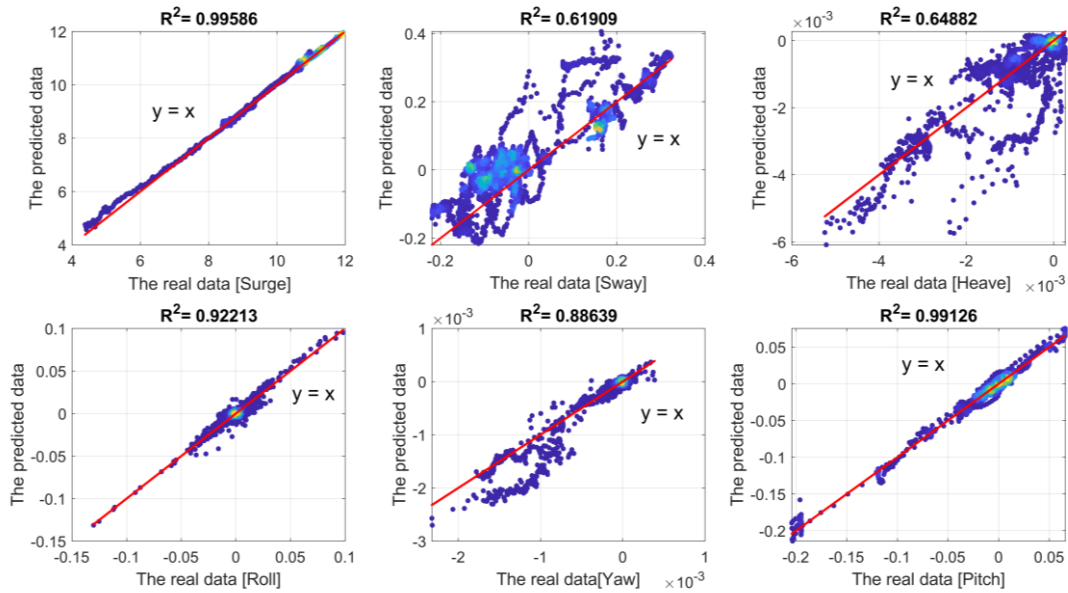


Figure 21. The results of the performance evaluation using R^2 value.

5.3. Applications description

As a first step toward demonstrating the benefits of an AI-based digital twin in this section, the models outlined in Section 5.1 are applied to predict ship fuel consumption and to estimate ship turning circles in calm sea conditions.

5.3.1. Ship fuel consumption prediction

To expand the applicability of the trained model to a subsequent voyage of the same ship (refer to Table 2), the new data stream was collected from January 2023 to June 2023. This new data stream encompasses eight entire voyages worldwide, as illustrated in Figure 22. The longest trajectory among these voyages is 7223.9 nautical miles, while the shortest one is 980 nautical miles. Voyage details are provided in Table 6. Utilizing the accumulated navigation data, ship operating conditions, engine operating conditions, and Metocean observations, the report leveraged the predictive capabilities of the trained model to estimate fuel consumption for this specific itinerary.

As shown in Figure 22, the trained ship fuel consumption model was loaded and then ship fuel consumptions of 8 whole voyages were predicted based on the trained model in time domain. For example, Figure 23 highlights that more than 90 % of the prediction errors are below 10 %, and the average error of the ship fuel consumption of the whole voyage 1 is measured at -0.51 %. Furthermore, the evaluation metrics (R^2 , RMSE, MAE and average error rate) are used to present the different between the real and the predicted ship fuel consumptions. The results of generalization ability evaluation were presented in Table 7. The results, as presented in Figure 24, reveal the outcomes of fuel consumption predictions. These results indicate that the R^2 values range from 0.71 to 0.94. Voyage 2 exhibits the smallest Mean Absolute Error (MAE) at 28.19 L/h, and the Root Mean Square Error (RMSE) for voyage 2 is also the lowest at 38.99 L/h. Furthermore, the average error rate values range from -0.51% to 5.56%, and the smallest average error rate of -0.51% is observed in voyage 1.

These findings affirm the viability of deploying the trained model as an efficacious tool for forecasting fuel consumption during comparable voyages. Consequently, the application of the trained model holds the potential to furnish valuable insights and facilitate efficient fuel management and optimization endeavors in real operational conditions.

Table 6. The general information of 8 whole voyages.

	Condition	Departure / destination	Voyage lengths	Number of data
Voyage 1	Laden condition	Vancouver / Yantai	7223.90 nm	28,479
Voyage 2	Ballast condition	Yantai / Hong Kong	980.22 nm	6,081
Voyage 3	Laden condition	Hong Kong / Sarina	3035.639 nm	17,347
Voyage 4	Ballast condition	Sarina / Singapore	3764.36 nm	19,545
Voyage 5	Laden condition	Singapore / Pouad	4724.23 nm	19,749
Voyage 6	Laden condition	Pouad / Rotterdam	3954.41 nm	8,299
Voyage 7	Ballast condition	Rotterdam/ Belem	4230.67 nm	19,930
Voyage 8	Laden condition	Belem / Rotterdam	4197.65 nm	21,206

Table 7. Generalization ability evaluation for different global voyages.

	Voyage 1	Voyage 2	Voyage 3	Voyage 4	Voyage 5	Voyage 6	Voyage 7	Voyage 8
R^2	0.84	0.73	0.88	0.71	0.94	0.94	0.92	0.80
RMSE (L/h)	53.24	38.99	61.02	72.72	29.09	57.33	42.14	86.14
MAE (L/h)	39.99	28.19	42.54	58.05	19.89	41.50	28.47	59.67
Average error rate	-0.51%	2.64%	-2.68%	5.56%	2.53%	1.36%	2.48%	-3.59%

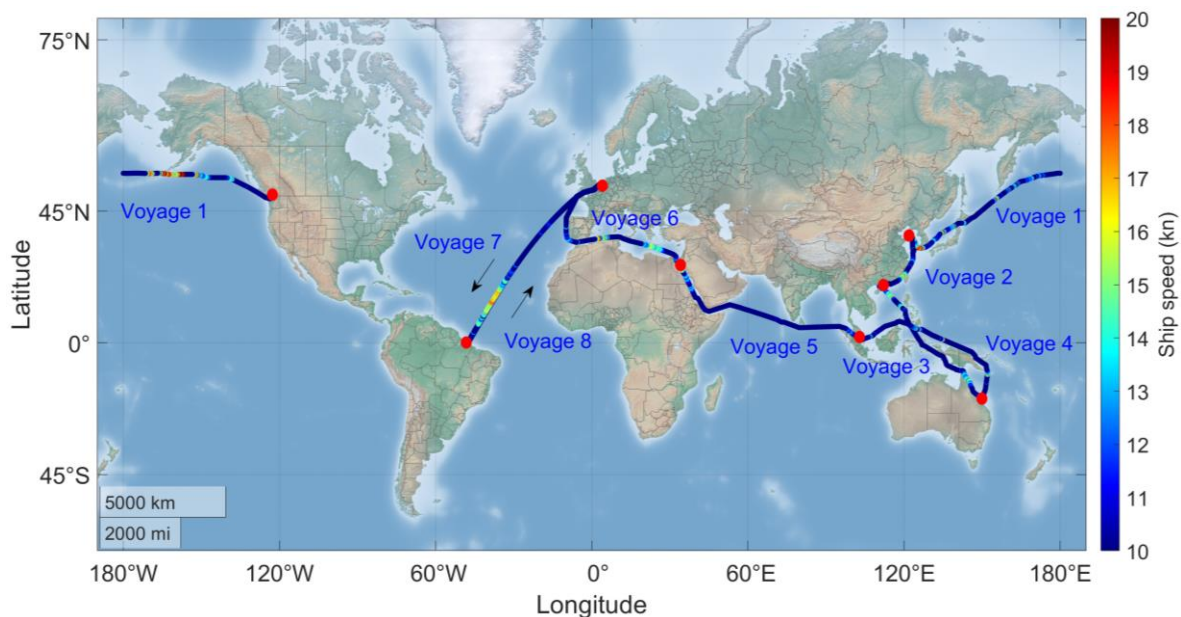


Figure 22. Ship fuel consumption prediction by calling the trained model. (Ship trajectories of new data of a bulk carrier from 01.2023 to 06.2023.)

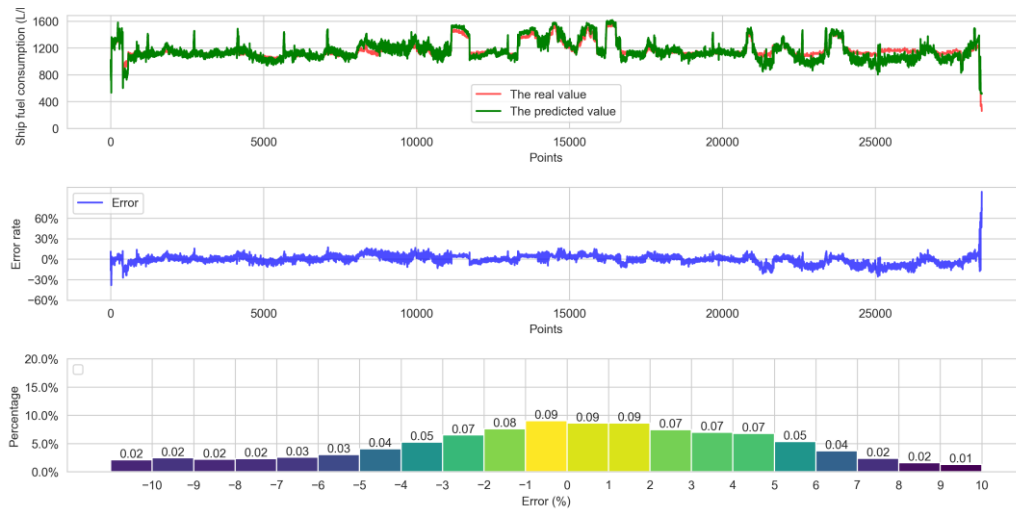


Figure 23. The error analysis of ship fuel consumption prediction for a whole voyage 1 (In the upper figure, the red line represents the real values of ship fuel consumption, while the green line represents the predicted results. In the middle figure, the blue line represents the error rate in the time domain. The bottom figure presents the prediction error distributions.)

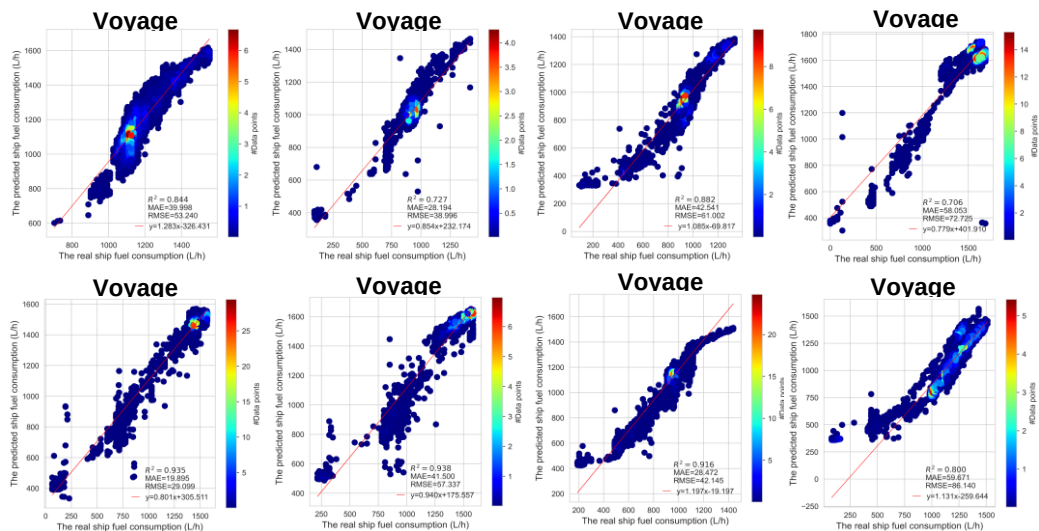


Figure 24. The comparison of the real and the predicted ship fuel consumption.

5.3.2. Turning circles prediction using the digital twin of the ship motion system

To demonstrate the generalization capability of the digital twin of the ship motion system, the prediction of ship motion dynamics was conducted by setting stable rudder angles as new inputs to generate turning circles. The selected stable rudder angles were set at 1° , 5° , 10° , and 15° (starboard), while the propeller revolutions were fixed at 109 rpm. Figure 25 illustrates the predicted turning circles for different rudder angles (1° , 5° , 10° , and 15°). The results indicate that the trained digital twin model can capture the turning characteristics of the ship accurately, despite not being explicitly trained on ship turning circle data. This suggests that the model has effectively "learned" the ship maneuvering features and can generalize well to new scenarios. Figure 26 presents an error analysis of turning circle predictions for various rudder angles (1° , 5° , 10° , and 15°). The analysis reveals that the predicted error increases as the rudder angle increases. This can be attributed to the fact that a significant majority (96.8%) of the rudder angles in the trained datasets fall within the range of -1° to 1° , as depicted in Figure 27. Consequently, as the rudder angle deviates from this range, the number of available training data points decreases, resulting in lower accuracy for turning circle predictions with higher rudder angles. To further improve the accuracy of the digital twin of the ship motion system in predicting turning circles for high rudder angles, it is suggested to train the model with more complex voyages that involve ship motion

dynamics in real conditions. By incorporating such data into the training process, the model can learn to handle the complexities and variations associated with higher rudder angles, enhancing its accuracy and performance.

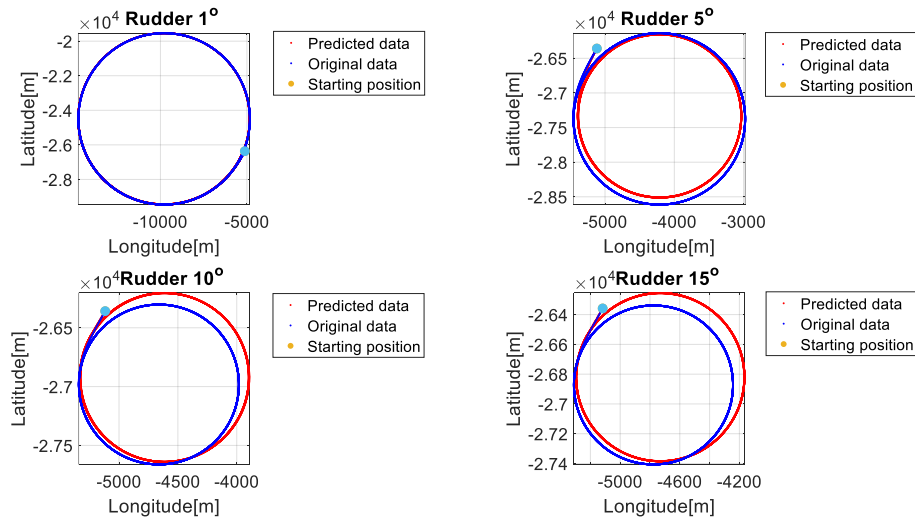


Figure 25. The prediction of the ship turning circle using the designed digital twin model.

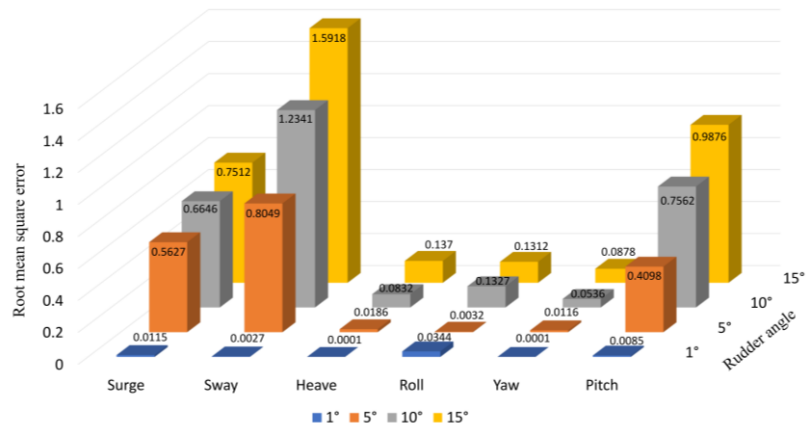


Figure 26. The error analysis of turning circle prediction at different rudder angles.

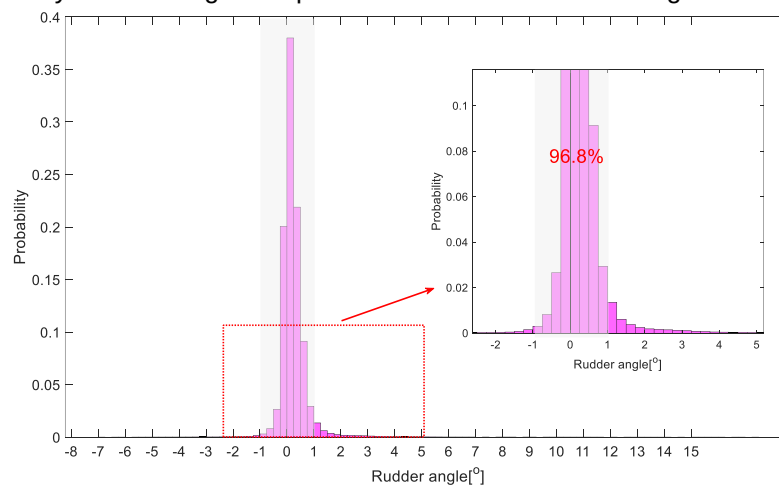


Figure 27. The distribution of the rudder angles of the trained data. The window demonstrates that distribution ranges from [-1 to 1].

6. Conclusions

The report introduces a ship digital twin model to enhance safe and sustainable ship operations. This ship digital twin consists of two distinct sub models. Sub model 1 incorporates a bi-directional LSTM network with attention

mechanisms to create a digital twin model of the ship's energy system. This model estimates ship fuel consumption under real operational conditions. Sub model 2 employs a transformer neural network to construct a digital twin model of the ship's motion system, enabling analysis of ship motions in relation to hydrometeorological conditions. The ship digital twin was trained, validated, and tested using bulk carriers and Ro-Pax ships as focal points. Key conclusions derived from the study can be summarized as follows:

- The innovative use of the multi-objective AI-based digital twin model for predicting ship motions and ship fuel consumption holds significant promise and utility in ensuring safe and sustainable ship operations.
- Sub model 1 of the AI-based ship digital twin learns the ship energy systems and can be utilized to estimate long-term ship fuel consumption under real operational conditions.
- Sub model 2 of the AI-based ship digital twin identifies the ship manoeuvring system accounting for realistic hydrometeorological conditions. It can accurately predict dynamics in real conditions between two ports, as well as ship turning circles with various rudder angles under calm conditions.
- High-frequency sea tail data streams are invaluable for constructing ship digital twins, and the proposed deep learning methods effectively capture the complex relationships between external conditions, internal conditions, and ship performance.

In the future, the utilisation of digital twin models in ship operations will provide comprehensive insights for proactive risk management, and optimized fuel consumption. While the preliminary results presented in this report are promising, it is important to note that they are limited to specific ship types. Extensive testing is necessary to generalize the suitability of the methods and a comprehensive framework for the appropriate utilization of digital twin technology in fleet management.

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