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comparative study of empirical, physical and ai models for predicting ship fuel consumption under real hydrometeorological conditions

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ABSTRACT

With the global maritime industry striving to reduce fuel consumption and emissions, accurate prediction models have become essential for optimizing ship operations under varying environmental conditions. This paper presents a comparative analysis of artificial intelligence (AI), semi-empirical, and physical models for predicting ship fuel consumption, with a particular focus on hydrometeorological influences. While empirical and physical models have traditionally been relied upon for estimating ship resistance and fuel consumption, recent AI advancements offer potentially superior alternatives in accuracy and adaptability. This research examines AI potential to either complement or exceed the performance of established methods, potentially setting new solutions for maritime fuel consumption prediction. Case studies are conducted on a Kamsarmax bulk carrier operated by Laskaridis Shipping Co. Ltd. The results reveal that the semi-empirical model, grounded in theoretical principles and empirical relationships, provides moderate accuracy in predicting ship fuel consumption. The physical model significantly improves predictive performance by incorporating dynamic simulations of ship behavior under varying sea conditions, using detailed hydrodynamic principles. In comparison, the AI-based model achieves the highest precision, demonstrating its ability to capture complex, nonlinear interactions and adapt to diverse operational scenarios. These findings highlight the transformative potential of AI in ship fuel consumption modeling, showing its capacity to set new benchmarks for efficiency and decision-making in maritime operations. This study mya provide valuable insights for improving weather routing and operational decision-making, affirming AI transformative impact in maritime engineering.

Keywords: Comparative study, ship fuel consumption prediction, AI, semi-empirical model, physical model, hydrometeorological conditions

1. INTRODUCTION

Maritime transport is a cornerstone of global trade, facilitating over 80% of worldwide cargo movement and playing a critical role in sustaining economic growth [1]. While the sector is often regarded as a relatively safe and environmentally cleaner mode of transportation [2][3], it faces increasing pressure to decarbonize in line with the Paris Agreement's climate objectives [4]. According to the International Maritime Organization (IMO), shipping accounted for 2.89% of global anthropogenic greenhouse gas (GHG) emissions in 2018 [5][6]. To achieve the IMO's ambitious target of reducing GHG emissions by 2050 relative to 2008 levels, it is essential to develop strategies that include retrofitting existing vessels and enhancing the energy efficiency of new ship designs.

An essential tool for this effort is a robust ship performance evaluation model capable of predicting ship energy consumption, optimizing routes, and ultimately minimizing fuel consumption and GHG emissions. These models can be categorized into three main types: (a) semi-empirical models, (b) physical models, and (c) artificial intelligence (AI)-based models, each with distinct advantages and limitations.

Empirical models, including semi-empirical approaches, rely on historical data and regression models to approximate ship fuel consumption (SFC). They employ simplified mathematical equations to balance computational efficiency and accuracy, making them practical for real-world applications. For instance, calm water resistance, influenced by frictional and viscous effects, and added resistance due to waves, wind, and obstacles are critical components in these models [7][8]. Common methodologies include the Holtrop and Mennen (1982) model [9], ITTC (2002) approaches [10], and their derivatives [11][12]. Despite their utility, empirical models often struggle to capture complex interactions or rare conditions accurately. Physical models adopt a hydrodynamic perspective to simulate ship behavior and predict fuel consumption under diverse conditions. These models, such as those proposed by Tillig and Ringsberg

(2019) [13] and Kim et al. (2023) [14], incorporate ship resistance and propulsion efficiency alongside external forces like waves and wind. While highly accurate, physical models are resource-intensive, requiring substantial computational power and time, limiting their applicability in large-scale or real-time scenarios. AI-based models leverage advancements in machine learning (ML) and big data to overcome limitations of empirical and physical methods [15]. These models analyze extensive datasets—including AIS data, voyage reports, and sensor readings—to predict SFC under realistic operational conditions [16]. Techniques such as supervised and unsupervised machine learning methods, as well as deep learning methods, have demonstrated significant potential for modeling complex interactions among influencing factors, including navigational patterns, ship operational states, and hydrometeorological conditions [17][18][19]. However, sensitivity to input variability and the complexity of training AI models remain challenges.

This paper presents a comprehensive overview of empirical, physical, and AI-based models for predicting ship fuel consumption, conducting a comparative analysis of their performance under real hydrometeorological conditions. The practical application of the proposed methodologies is demonstrated through big data records obtained from sea trials of a bulk carrier operated by Laskaridis Shipping Co. Ltd. By critically examining the strengths, limitations, and applicability of each approach, this study provides valuable insights into the optimal selection and integration of predictive models for enhancing fuel efficiency and minimizing emissions in maritime transportation.

2. FULL SCALE CASE STUDY SHIP

To evaluate the adopted typical semi-empirical, physical, and AI-based models, extensive big data records from sea trials of a Kamsarmax bulk carrier operated by Laskaridis Shipping Co. Ltd. were employed, as detailed in Tables 1-5. The dataset covers a two-year period (February 2021 to January 2023), encompassing a wide range of operational and environmental conditions (Figure 1). It consists of over 1 million data records, with each record containing 266 parameters [15]. Data were collected at 60-second intervals, providing high-resolution temporal data essential for the robust development of the proposed models. This comprehensive dataset ensures that the models are tested against realistic scenarios, enhancing their applicability and reliability in real operational conditions.

TABLE 1: SHIP SPECIFICATION OF THE KAMASARMAX CLASS BULK CARRIER.

Length overall	229.00 m
Length between perpendiculars	225.50 m
Breadth, moulded	32.26 m
Depth, moulded	20.05 m
Summer load line draught, moulded	14.45 m
Deadweight at summer load draught	80996.1 t
Draft (T)	12.6 m
Longitudinal Center of Gravity (XG)	-14.1 m
Block Coefficient (CB)	0.879
Vertical Center of Gravity (KG)	11.51 m
Metacentric Height (GM)	2.5 m

TABLE 2: MAIN CHARACTERISTICS OF THE MAIN ENGINE.

Manufacturer	HYUNDAI-MAN B&W
Type	6S60ME-C8.5
Maximum continuous rating (MCRME)	9930 kW x 90.4 rpm
Limited maximum continuous rating with engine power limitation (MCRME,lim)	8230 kW
SFC at 75% of MCRME or 83% of MCRME lim	166.81 g/kWh
Number of engines	1
Fuel type	HFO

TABLE 3: HYDRODYNAMIC PROPERTIES.

Longitudinal Center of Flotation (LCF)	9.3 m
Longitudinal Metacentric Height (GML)	296.7247 m
Waterplane Area (AWP)	6981.6453 m^2
Wetted Surface Area (SWET)	12513.5261 m^2

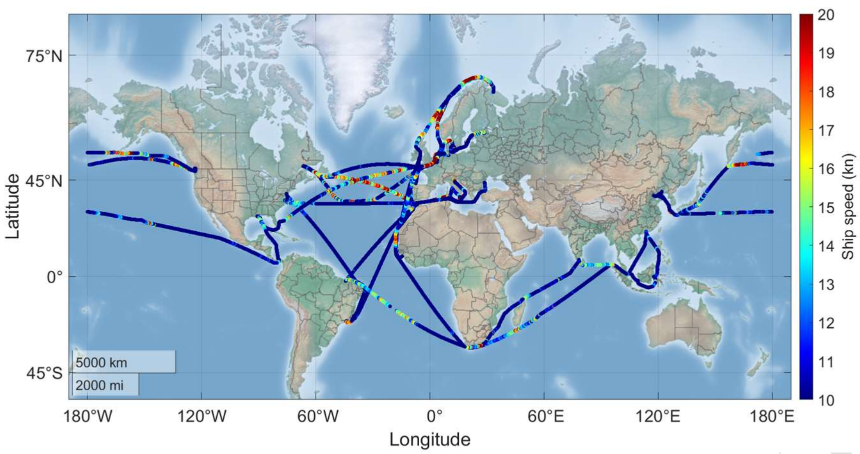

FIGURE 1: SHIP TRAJECTORIES OF SEA TRIAL DATA OF A BULK CARRIER FROM 01.2021 TO 02.2023.

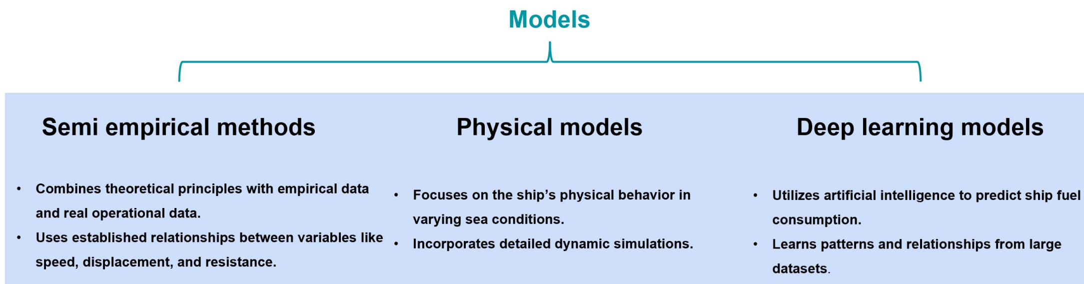

FIGURE 2: THE SHIP FUEL CONSUMPTION PREDICTION MODELS USED FOR THE COMPARATIVE STUDY.

TABLE 4: MAIN CHARACTERISTICS OF THE RUDDER.

Rudder Area in X (AX):	574.0 m²
Rudder Area in Y (AY):	2050.0 m²
Rudder Coordinates (XR, ZR):	-114.5, 10.5 m
Rudder Aspect Ratio (AR):	1.50
Rudder Angle (ARUD):	45.0 deg
Viscosity Coefficient (VISC):	1.27E-6 m²/s
Rudder Gain (YRG):	0.0

TABLE 5: MAIN CHARACTERISTICS OF THE PROPELLER.

Propeller Diameter (D)	6.95 meters
Number of Propeller Blades (Z)	5.0
Added Mass Coefficient (KZZ)	0.0576
Added Mass Coefficient (KXX)	0.0033
Thrust Deduction Factor (TDF)	0.195
Wake Fraction	0.275
Developed area ratio (B)	0.52
Skew angle	24.5 deg
MCR	9930 KW
Shaft speed of propeller	90.4kw

3. METHODS

This section presents the methodologies adopted for predicting SFC, encompassing three distinct approaches: semi-empirical models, physics-guided models, and deep learning models. Each method offers unique advantages and challenges, contributing to a comprehensive evaluation framework, as shown in Figure 2. Section 3.1 presents the semi-empirical model, which uses simplified equations based on historical data for efficient and practical predictions. Section 3.2 covers physics-guided models, integrating physical principles with empirical data and machine learning for enhanced accuracy. Section 3.3 focuses on deep learning models, highlighting their ability to capture complex, nonlinear relationships in large datasets for detailed and adaptive predictions. These methods collectively provide the basis for a comparative analysis of SFC prediction under real hydrometeorological conditions.

3.1 Semi-empirical model

The propulsion system of a ship primarily encompasses energy consumption for propulsion, auxiliary systems, and heating. The Figure 3 presents the flowchart of semi-empirical model for the fuel consumption estimation of ship propulsion system. In navigating real sea conditions, ship fuel consumption is influenced by several variables, including engine parameters, propeller characteristics, and the resistance experienced by the vessel. Ship propulsion power correlates closely with its velocity and the encountered operational conditions. The conventional estimation of ship propulsion power and fuel consumption involves sequentially calculating resistance and power requirements. Resistance at varying speeds is determined through model testing, computational methods, or semi-empirical formulations. Additional resistance induced by wind and waves, typically encountered during most voyages, is integrated into the total resistance calculation. This resistance must be counteracted by the propulsive force, which is derived from the ship's engine power transmitted through the propeller system.

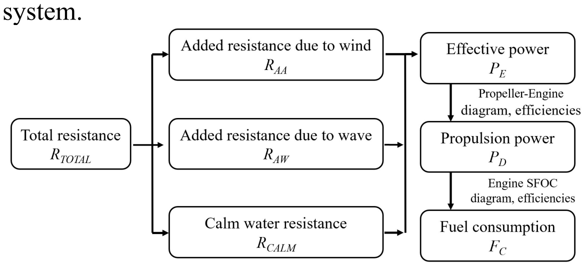

FIGURE 3: THE FLOWCHART OF SEMI-EMPIRICAL MODEL FOR THE ESTIMATION OF SHIP PROPULSION SYSTEM.

The total Resistance in real seaways can be determined as the sum of calm water resistance, wind-induced resistance, and wave-induced resistance. An approximate method was proposed for evaluating resistance in calm water based on ship geometry, appendages, and immersion characteristics [9]. This resistance (R_{CALM}) is the sum of several components:

$$R_{CALM} = R_F(1 + k_1) + R_{APP} + R_W + R_{other} \tag{1}$$

Here, R_F is the frictional resistance determined using ITTC-1957 standards [10]. The remaining components, including appendage resistance (R_{APP}), wave resistance (R_W), and others (bare hull, bulbous bow, immersed transom, and model ship correlation resistance), are estimated via empirical formulas or test data, which may offer greater accuracy for specific ship types. In this study, appendage resistance (R_{APP}), wave resistance (R_W), and R_{other} was calculated based on the test data of the case study ship mentioned in section 2.

Resistance caused by wind depends on the superstructure exposed area and relative wind conditions. Using the ISO (2015) guideline [20], the wind resistance (R_{AA}) is calculated as:

$$R_{AA} = \frac{1}{2}\rho_A\left[C_{AA}(\varphi_{WR})A_{XV}{V_{WR}}^2 - C_{AA}(0)A_{XV}{V_g}^2\right] \tag{2}$$

Here, ρ_A denotes air density, A_{XV} represents the transverse projected area above the waterline, and V_{WR} and V_g are the relative and ground speeds, respectively. C_{AA} is the wind resistance coefficient adjusted for the wind direction (φ_{WR}).

The added resistance caused by waves (R_{AW}) integrates wave spectrum data with transfer functions. For irregular seas, it is expressed as:

$$R_{AW}(\omega|H_s,T_p,\gamma,V,\beta) = 2\int_0^{\infty}\int_{-\frac{\pi}{2}}^{+\frac{\pi}{2}} S\left(\omega|H_s,T_p,\gamma\right)\frac{R_{aw}(\omega|V,\beta)}{\zeta_a(\omega)^2}D(\theta-\beta)d\theta d\omega \tag{3}$$

Here, S is the wave spectrum characterized by significant wave height (H_s) and peak period (T_p), β denotes the relative wave angle, and D(θ) represents a directional spreading function.

$$S(\omega|H_s,T_p,\gamma)D(\theta) = \frac{320{H_s}^2}{T_p^4\omega^5}exp\left(\frac{-195}{{T_p}^4\omega^4}\right)\gamma^{exp\left[\frac{-(\omega-\omega_p)^2}{2\sigma^2\omega_p^2}\right]}D(\theta) \tag{4}$$

$$D(\theta) = \begin{cases} \dfrac{2}{\pi}\cos^2(\theta) & \text{for } -\dfrac{\pi}{2} \le \theta \le \dfrac{\pi}{2} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Based on the total resistance calculated by Eqs. (2-5), the effective power (P_E) needed to overcome the total resistance (R_{TOTAL}) at a given speed (V) is defined as Eq. (6). The relationship between engine brake power (P_B), propeller efficiency, and effective power is expressed as Eq. (7).

$$P_E = R_{TOTAL} \cdot V \tag{6}$$

$$P_B = \frac{P_D}{\eta_s} = \frac{P_E}{\eta_s \cdot \eta_h \cdot \eta_r \cdot \eta_o} \tag{7}$$

Here, P_D represents propulsion power, while η_s, η_h, η_r, and η_o denote efficiencies related to the shaft, hull, relative rotation, and open water, respectively. By incorporating specific fuel consumption (SFOC) and operational duration, fuel usage can be estimated for various conditions. In this study, the above parameters were collected based on ship sail tail data of the case study ship mentioned in section 2.

Finally, ship fuel consumption can be determined by Eq. (8).

$$SFC = \frac{3600 \times P_B \cdot SFOC}{1000 \times \rho} \tag{8}$$

The unit of SFC is L/h (liters per hour). ρ is fuel density. SFOC is typically expressed in grams of fuel consumed per kilowatt-hour (g/kWh) of energy produced by the engine. The value is 160–180 g/kWh. In the paper, the initial SFOC is shown in Table 2 and the real value is updated by real ship fuel consumption records.

Overall, to estimate fuel consumption using above empirical formulas, a total of 22 parameters are required as mentioned in Eqs (1-8). These include components for resistance calculations, such as calm water resistance R_{CALM}, wind resistance R_{AA}, and wave-induced resistance R_{AW}, which together require 16 parameters of the target ship (e.g., air density, projected area, wave spectrum characteristics, and relative speeds). Additionally, propulsion power estimation involves 4 efficiency-related parameters ($\eta_s \cdot \eta_h \cdot \eta_r \cdot \eta_o$), while fuel consumption calculation requires 2 parameters: the SFOC and operational duration. These parameters are crucial to accurately determine ship fuel usage under real sea conditions.

3.2 Physics-guided ship fuel consumption prediction models

The developed ship physical method for evaluating ship performance integrates comprehensive environmental and operational data with advanced ship manoeuvring systems modelling and machine learning techniques to provide accurate and reliable forecasts. The framework outlined in the diagram systematically addresses various aspects of ship operation, combining them into a cohesive process that enhances prediction accuracy and operational efficiency, see Figure 4.

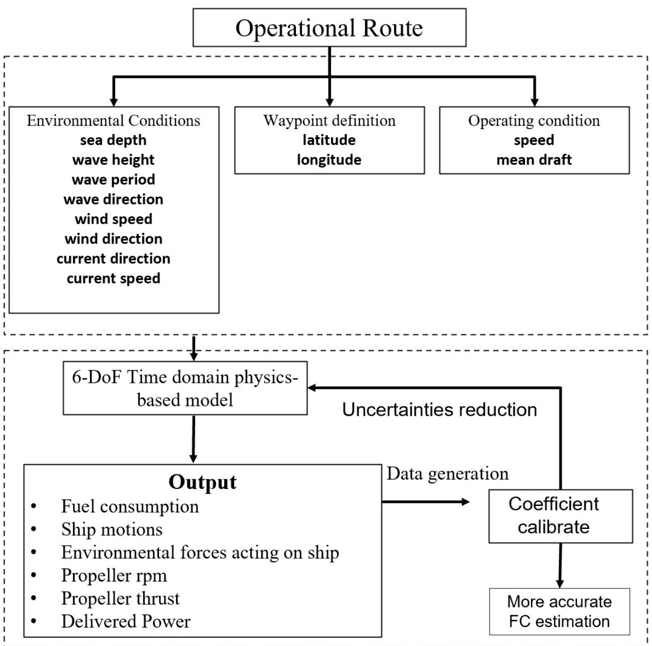

FIGURE 4: THE FRAMEWORK OF THE DEVELOPMENT OF THE SHIP PHYSICAL MODEL FOR THE EVALUATION OF SHIP PERFORMANCE.

The following explanation aims to delineate each component of the framework, highlighting their roles and interactions.

1) Input data collection

The framework begins with the collection of extensive input data during the voyage. This data is categorized into three main segments: (a) Environmental Conditions: Parameters such as sea depth, wave height, wave period, wave direction, wind speed, wind direction, current direction, and current speed are crucial. These variables provide a detailed understanding of the external forces acting on the ship. (b) Waypoint Definition: The latitude and longitude coordinates that define the ship route. This geospatial data is essential for mapping the ship route and integrating environmental conditions specific to each location. (c) Operational Conditions: Information on the ship speed and mean draft. These operational parameters are vital for assessing the ship performance and fuel consumption under different conditions.

2) 6-DoF time domain physics-based model

The core of the framework is the Six Degrees of Freedom (6-DoF) time domain physics-based model. This model can be used to stimulate the main characteristics of the target ship and her manoeuvring systems. This model simulates the ship motions under varying sea conditions by considering the environmental and operational inputs. It outputs several critical performance metrics: (a) Fuel consumption, (b) 6 DOF ship motions, (c) Environmental forces acting on the ship, (d) Propeller RPM, (e) Propeller thrust, and (f) Delivered power. These outputs provide a detailed assessment of the ship's performance, helping in understanding how different factors or ship motions influence fuel consumption.

3) Uncertainty reduction and coefficient calibrate

To calibrate the coefficients of the ship physical model, the framework incorporates uncertainty reduction techniques and machine learning (ML) training. The uncertainty reduction techniques of the 6-DoF model are used to calibrate coefficients using the regression method based on the historical operational records of the case study ship. This process involves: (1) Refining the parameters of a 6-DoF model to minimize errors and improve the reliability of predictions compared to the actual operations of the target ship. (2) Leveraging regression method to learn patterns and relationships between inputs and outputs. This step is crucial for improving the predictive accuracy of the fuel consumption prediction model. The integration of physics-based modeling and ML techniques leads to more accurate fuel consumption estimations. The calibrated coefficients and trained models are used to refine the initial predictions of the specific ship, providing more precise and reliable outputs. This iterative process ensures that the model remains robust and adaptive to varying conditions.

The ship physical method framework combines detailed environmental and operational data with sophisticated modeling and machine learning approaches to predict ship fuel consumption accurately. By systematically addressing the complexities of ship operations and environmental interactions, this method provides valuable insights for optimizing fuel usage, reducing operational costs, and promoting sustainable maritime practices. This comprehensive approach underscores the importance of integrating multiple data sources and advanced analytical techniques in maritime research and ship operation optimization.

3.2.1 A 6-DoF ship dynamics model

Physical guided ship fuel consumption prediction models rely on the integration of physical principles and empirical data to accurately estimate the fuel consumption of ships under varying operational and environmental conditions. These models often combine theoretical frameworks with machine learning to ensure robust and reliable predictions.

The nature of the physics model for ship fuel consumption predictions is a 6-DoF ship manoeuvring model. The workflow of this 6-DoF ship manoeuvring model is illustrated in Figure 5.

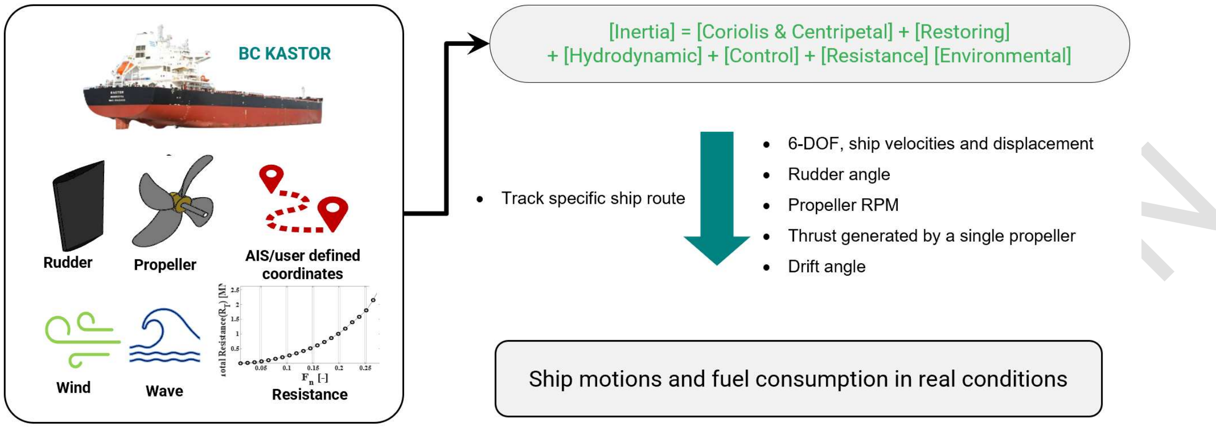

FIGURE 5: THE FLOWCHART OF THE 6-DOF SHIP DYNAMICS MODEL FOR THE PREDICTION OF SHIP FUEL CONSUMPTION.

The 6-DoF manoeuvring model integrates ship parameters (rudder, propeller, hull resistances, etc.) and environmental conditions to predict ship motions and ship fuel consumption in real operational conditions. The model requires detailed parameters from the target ship, including rudder and propeller specifications, user-defined coordinates, resistance data, and environmental factors such as wind and waves. It considers various operational conditions, including deep sea, shallow water, calm waters, short waves manoeuvring, and wind/aerodynamic forces, for both single and twin-screw rudder propeller configurations, see more in the study [21]. The model utilizes a comprehensive set of dynamic equations accounting for inertia, Coriolis and centripetal forces, restoring forces, hydrodynamic effects, control inputs, resistance, and environmental loads. In addition, the physics-guided model accounts for propeller-hull interaction and shaft efficiency through calibrated coefficients. These coefficients have been refined based on sea trial data and real operational data. This approach ensures accurate evaluation of ship performance and predictions of ship fuel consumption, validated across multiple operational conditions. Overall, the presented 6-DOF ship manoeuvring model has the following features/applications: Deep water manoeuvring, Wind forces, Single and Twin rudder-propeller configuration, 6-DOF motion, surge, sway, heave, roll, pitch, and yaw, Short Waves (λ /L ≤ 0.5 and H_sw ≤ 2m), Shallow Water Effects (Increase in ship resistance and changes in hydrodynamic forces), Ocean Currents, Roll moment resulting from wind forces.

The 6-DoF ship dynamics model is designed to predict fuel consumption and assess vessel performance by incorporating environmental factors, waypoint definitions, and operational parameters. This physics-based framework evaluates the impact of external conditions and dynamic ship responses. Wind-related inputs include speed and angle relative to an earth-fixed reference frame, while shortwave data encompass wave height, period, and direction. In extreme scenarios, aerodynamic forces significantly influence ship behavior, with wind loads calculated using the Blendermann method [22]. The model also integrates shallow water effects and shortwave forces, as described by Taimuri et al. (2020) [21]. Comprehensive ship-specific details for the dynamics model are provided in Section 2.

Based on these inputs, the vessel trajectory is governed by an autopilot control system [23]. The rudder adjusts the course to maintain the desired heading set via AIS data. A Proportional Derivative (PD) controller determines the target rudder angle (δ_T)) to align the ship heading (ψ_d) as defined by Eq. (9) [24]. The autopilot controller uses a linear differential equation (Eq. (10)) to calculate rudder adjustments, where ω_δ represents the rudder's turning rate. To achieve the target speed (U_d), a P-controller modulates the ship propeller revolutions. Initially, the propeller rotational speed is set based on the vessel current speed (U), as outlined in prior research [10]. The updated propeller rotation rate ($N_{rp\ new}$) is calculated using Eq. (11), derived from navigation data and desired operational conditions.

$$\delta_T = K_p(\psi - \psi_d) + K_D\dot{\psi} \tag{9}$$

$$\dot{\delta} = sgn(\delta - \delta_T)\omega_\delta \tag{10}$$

$$N_{rps_{new}} = \frac{-k_{T1}V_A\rho D^3 + \sqrt{(k_{T1}V_A\rho D^3)^2 + 4k_{T0}\rho D^4\left(V_A^2\rho D^2 k_{T2} - X_{Prop_{new}}\right)}}{2k_{T0}\rho D^4} \tag{11}$$

where K_P and K_D are the gain factors of autopilot. k_{T0}, k_{T1}, and k_{T2} are 2nd-order polynomial coefficients of propeller thrust characteristics curve having the propeller diameter of D. $X_{Prop_{new}}$ is the desired propeller thrust at the ship advanced speed of V_A ($V_A = (1 - w)U_d$).

The new propeller revolution per second N_{rps_i} (RPS) is defined as Eq. (12).

$$N_{rps_i} = K_{p_{rev}}(U_d - U) + N_{rp\ new} \quad (12)$$

where, $K_{p_{rev}}$ is the proportional gain of the P-controller. Consequently, the ship control devices (rudder angle, propeller rpm), and ship motion dynamics under the influence of environmental conditions are generated in real conditions.

3.2.2 Ship fuel consumption calculations

This comprehensive data collection enables the detailed analysis and understanding of the ship performance under various operational conditions, facilitating optimized ship handling and fuel efficiency, see more in the previous paper [15] and the data in Fig. 1 and Section 2. Based on the 6-DoF ship dynamics model, utilizing the specified input data, the model can generate the following outputs: 6-DOF ship velocities and displacement, Rudder angle, Propeller RPM, Thrust generated by a single propeller, Drift angle of the vessel. Then, the total power required of the target ship can be calculated by using the Eq. (13). Finally, ship fuel consumption can be determined by the Eq. (8). In this model, the initial value is set to 1 g/kWh and will be updated based on the specifications of the target ship.

$$Power = Thrust \times Z \times V \quad (13)$$

Where, Z represents the number of propellers and V denotes the vessel's surge speed.

The physical model for ship fuel consumption prediction of the selected case study ship encompasses a comprehensive set of parameters spanning multiple domains, including ship geometry, stability, propulsion, rudder characteristics, environmental conditions, and operational settings. Specifically, the ship geometry and stability parameters involve key dimensions such as length, breadth, draft, and coefficients like block coefficient and metacentric heights. The propulsion system parameters cover engine performance metrics, propeller characteristics, and efficiency coefficients. Rudder parameters include rudder area, aspect ratio, and control gains, while environmental conditions account for wind, wave, and current characteristics. Operational parameters incorporate ship speed, simulation time, and thrust coefficients. Overall, the model integrates approximately 76 parameters, reflecting its comprehensive nature and the level of detail required for accurate predictions of ship performance and fuel consumption under real-world operational conditions.

3.3 Deep learning model

To predict ship fuel consumption under real operational conditions, this section introduces a deep learning model based on based on Bidirectional Long Short-Term Memory (Bi-LSTM) networks with attention mechanisms, as illustrated in Figure 6. The model leverages the strengths of Bi-LSTM, which effectively captures both past and future dependencies, and attention mechanisms, which enhance the model's ability to focus on the most relevant portions of the input data streams. This combination enables the model to efficiently capture and utilize historical information, delivering robust predictive performance. Figure 6 and Table 6 outline the algorithm, detailing the step-by-step process, including data preprocessing, model architecture configuration, training, and prediction generation. The architecture of the ship fuel consumption prediction model, depicted in Figure 7, comprises four main components: (i) input layers, (ii) Bi-LSTM layers, (iii) attention layers, and (iv) the output layer. For further details, refer to Zhang et al. (2024) [15].

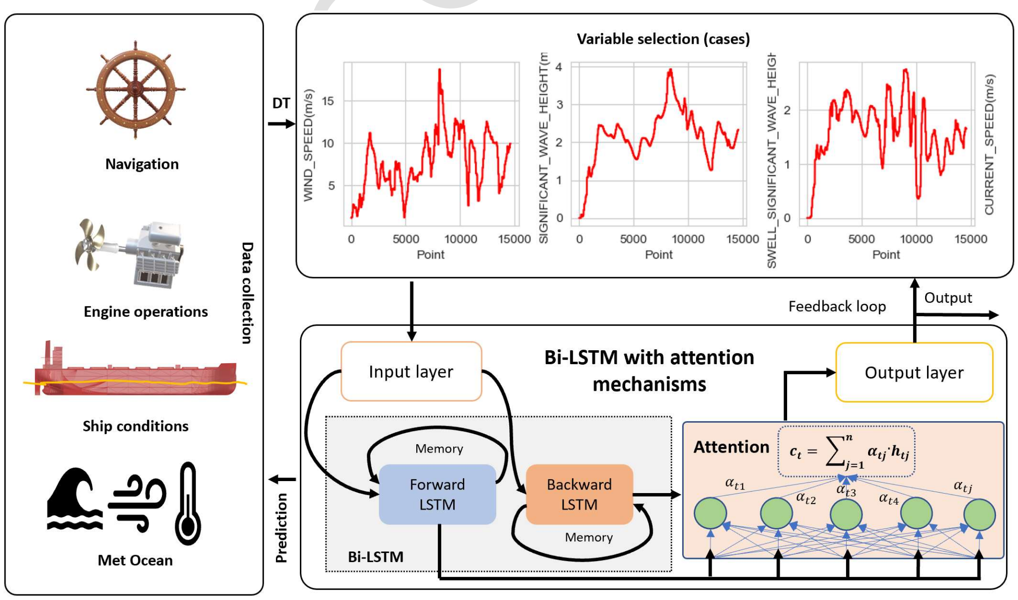

FIGURE 6: THE DEEP LEARNING METHOD ARCHITECTURE FOR SHIP FUEL CONSUMPTION PREDICTION.

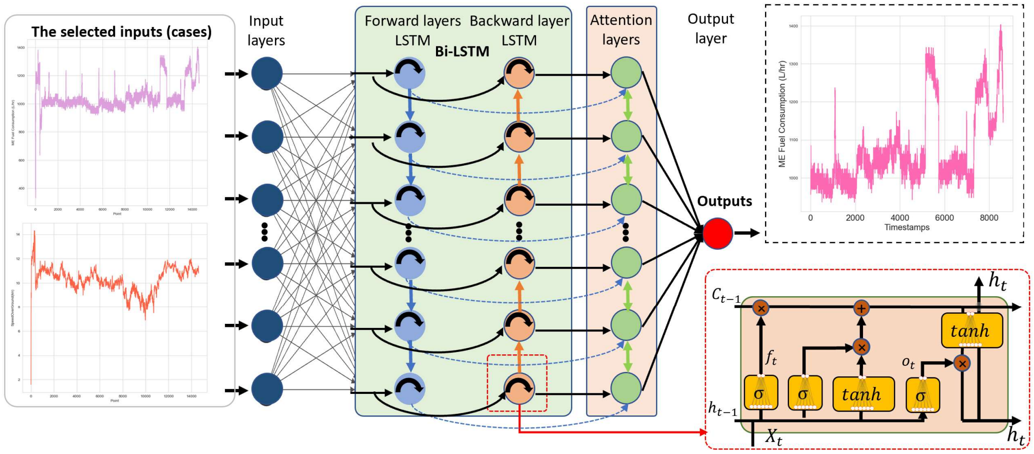

FIGURE 7: THE ARCHITECTURE OF Bi-LSTM WITH ATTENTION MECHANISM FOR SHIP FUEL CONSUMPTION PREDICTION.

To train the AI model, the inputs include ship navigation information (speed, course, heading), ship operation condition data (draft, trim), and engine operation parameters (propeller and main engine shaft RPM and torque). Additionally, external operational conditions are considered as primary control parameters or influencing factors for managing the ship's energy and navigation systems. Since the propeller and main engine shaft RPM and torque are closely related and interdependent, they are excluded from the input parameters. The output of the model is the ship's fuel consumption. For further details regarding model training and 5-fold cross validation, refer to Zhang et al. (2024) [15].

This study introduces a deep learning model, designed for high-precision prediction tasks. The model architecture consists of an input layer, three Bi-LSTM layers, three attention layers, and an output layer. Each Bi-LSTM layer comprises 128 hidden units, while the attention mechanism enhances the model ability to capture critical features. The model hyperparameters were optimized using grid search combined with 5-fold cross-validation. The final configuration includes the Adam optimizer, a learning rate of 5e-5, a batch size of 48, a dropout rate of 0.2, a regularization parameter of 0.1, and training over 178 epochs with early stopping (patience = 10). The total number of trainable parameters is 722,433 in this model.

To evaluate the performance and quantify the errors between the real and the predicted ship fuel consumption, Root Mean Square Error (RMSE), and error rate e_n are used as shown in Eqs. (14-15).

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n)^2} \tag{14}$$

$$e_n = (y_n - \hat{y}_n)/(y_n) \tag{15}$$

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

TABLE 6: 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
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 $data_{batch\ size}$
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_{tj} 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 real operational conditions
15 End For
16 Save the prediction model: AI-based ship fuel consumption prediction model

4. RESULTS

4.1 Data for comparative study

To validate the predictive accuracy of the three models introduced in Section 3—namely, the semi-empirical, physical, and AI-based models—data from a single laden voyage (Voyage 1) was employed. This voyage spanned the route from Vancouver, Canada, to Yantai, China, covering a total distance of 7223.90 nautical miles. Over the course of this voyage, a dataset consisting of 28,479 records was collected, capturing a broad spectrum of operational and environmental conditions. The data was recorded at regular intervals, ensuring high-resolution temporal granularity essential for robust model validation. Each record includes parameters critical to ship fuel consumption prediction, such as ship speed, draft, propulsion system metrics, and environmental conditions (e.g., wave height, wind speed, and current velocity). These parameters provide a comprehensive dataset for evaluating the models under realistic operational scenarios. However, certain challenges were encountered during the data preprocessing phase. Due to missing values in some parts of the dataset, only the first 19,000 data points, which were deemed complete and reliable, were used for model validation. Missing values were handled through estimation methods based on interpolation and statistical imputation to ensure data integrity. This subset was selected to minimize the impact of incomplete data on the model evaluation, ensuring a fair and consistent comparison across the three approaches.

The use of this dataset allowed for an in-depth assessment of the model performance under real-world conditions, providing a strong foundation for evaluating their predictive accuracy and robustness. The error metrics computed for each model, based on this voyage data, are presented in the subsequent sections to highlight the relative strengths and weaknesses of each approach.

4.2 Ship fuel consumption using semi-empirical model

The semi-empirical model demonstrated moderate accuracy in predicting ship fuel consumption, with a mean prediction error of -17.32%, an MSE of 75,589.01, and an RMSE of 274.93, as shown in Figure 8. This model, based on simplified equations derived from historical data and theoretical principles, effectively balances computational efficiency and practical application. However, its performance is hindered by an inability to capture complex, nonlinear interactions inherent in real-world operational conditions. The model's underestimation of fuel consumption highlights its limitations in representing dynamic environmental factors, such as fluctuating wave and wind conditions. As a result, while the semi-empirical model is suitable for quick estimations or scenarios with limited data availability, its applicability to high-precision tasks is limited.

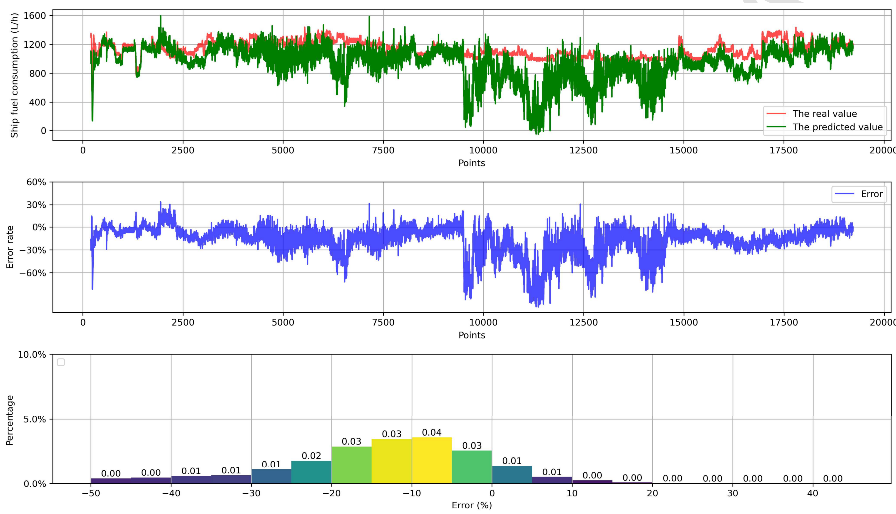

FIGURE 8: THE ERROR ANALYSIS OF SHIP FUEL CONSUMPTION PREDICTION USING SEMI-EMPIRICAL MODEL.

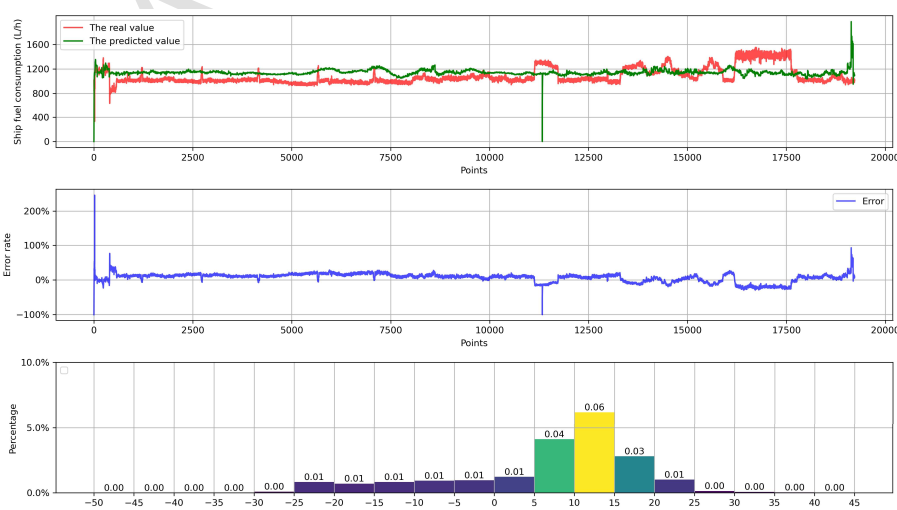

FIGURE 9: THE ERROR ANALYSIS OF SHIP FUEL CONSUMPTION PREDICTION USING PHYSICAL MODEL.

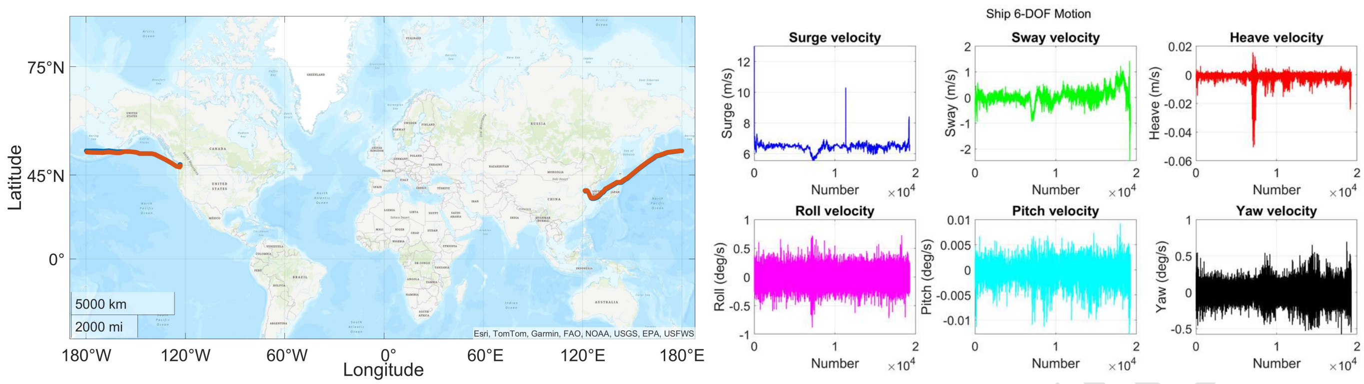

FIGURE 10: THE REAL AND THE PREDICTED SHIP TRAJECTORIES AND SHIP MOTIONS.

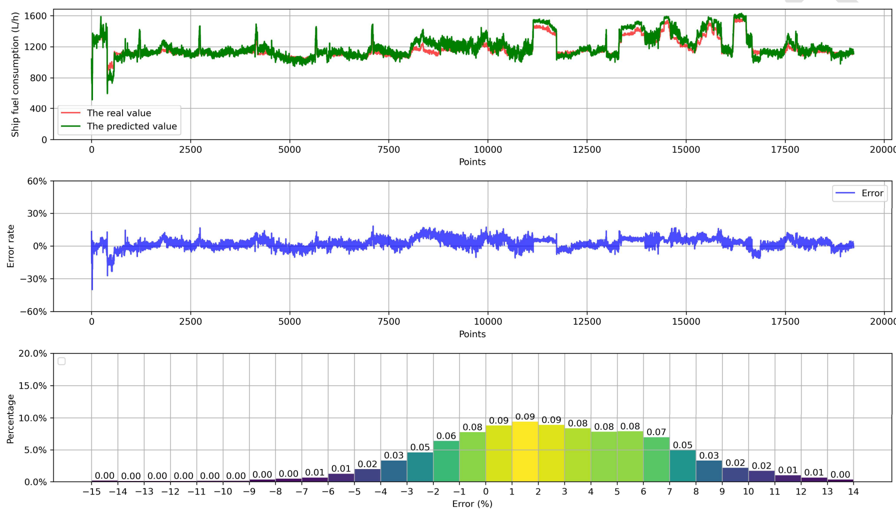

FIGURE 11: THE ERROR ANALYSIS OF SHIP FUEL CONSUMPTION PREDICTION USING DEEP LEARNING MODEL.

4.3 Ship fuel consumption using physical model

The physical model achieved significantly improved results compared to the semi-empirical approach, with a mean prediction error of 7.02%, an MSE of 23,754.37, and an RMSE of 154.12, as shown in Figure 9. By incorporating detailed hydrodynamic principles and environmental data, the model effectively captures critical factors such as wave-induced resistance, aerodynamic forces, and ship maneuvering dynamics. This higher level of physical fidelity allows for more accurate predictions under diverse and challenging operational conditions. Such capabilities make the physical model an excellent choice for detailed performance evaluations and scenario analyses in maritime operations.

Beyond predicting fuel consumption, the physical model demonstrates its versatility by simulating ship trajectories and six-degree-of-freedom (6-DOF) motions. For example, as shown in Figure 10, the orange trajectory represents the actual voyage path of Voyage 1, while the blue trajectory reflects the predicted path using the physical model. The close alignment between the two trajectories underscores the model's ability to simulate ship behavior under real hydrometeorological conditions, accounting for environmental interactions and operational constraints.

However, the physical model's reliance on high-quality input data and precise calibration introduces challenges, particularly in real-time applications. The computational demands for processing complex simulations can also limit its practicality in scenarios requiring rapid decision-making. Despite these limitations, the physical model remains a robust and reliable tool for maritime engineering, offering not only accurate fuel consumption predictions but also the ability to simulate detailed ship dynamics and operational scenarios. This dual capability positions the physical model as an indispensable resource for both predictive and diagnostic analyses in maritime operations.

4.4 Ship fuel consumption using AI based surrogate model

The AI-based surrogate model outperformed both the semi-empirical and physical models, achieving a mean prediction error of just 0.77%, an MSE of 4,529.85, and an RMSE of 67.30, as shown in Figure 11. Utilizing a Bi-LSTM network with attention mechanisms, this model excelled in capturing complex, nonlinear relationships between operational and environmental parameters. Its ability to process large datasets and adapt to diverse conditions highlights its transformative potential for maritime applications. The AI model scalability and accuracy make it ideal for real-time optimization and decision-making. However, its reliance on high-quality, extensive datasets and its "black-box" nature pose challenges in interpretability and transparency. While the AI-based approach is poised to redefine predictive modeling in maritime engineering, its application must be carefully managed to address these limitations.

Overall, the results highlight the distinct strengths and weaknesses of each model. The semi-empirical model offers simplicity and efficiency but lacks the sophistication needed for precise predictions. The physical model balances accuracy and interpretability at the cost of higher computational requirements. The AI-based model delivers unmatched accuracy and adaptability, making it the most promising for advanced applications. Future efforts could focus on hybridizing these approaches to leverage their respective advantages, combining the interpretability of physics-based methods with the predictive power of AI to achieve optimal performance in ship fuel consumption modeling.

5. CONCLUSION

This study offers a comprehensive comparative analysis of semi-empirical, physical, and AI-based models for predicting ship fuel consumption under real hydrometeorological conditions, using extensive sea trial data from a Kamsarmax bulk carrier. The results highlight significant differences in model performance, largely driven by the number of parameters considered in each approach and their ability to capture complex operational and environmental interactions.

The semi-empirical model, utilizing only 22 parameters, provides a computationally efficient solution suitable for scenarios with limited data availability. However, its simplified equations lead to an average prediction error of 17.3%, reflecting its inability to account for complex nonlinearities and dynamic environmental influences. In contrast, the physical model incorporates 76 parameters, enabling it to achieve a significantly improved error rate of 7.02%. By integrating detailed hydrodynamic principles and ship dynamics, this model offers greater accuracy but demands extensive data and computational resources, which can limit its practicality in large-scale or real-time applications. The performance difference between the semi-empirical and physics-guided models after data point Nr. 9000 stems from their fundamental approaches. The semi-empirical model neglects the ship system's integrity, making it less accurate under complex sea conditions. In contrast, the physics-guided model accounts for system coupling effects, enhancing robustness and maintaining higher accuracy across varying conditions.

The AI-based surrogate model, leveraging over 1.1 million factors from high-resolution datasets, outperformed the other approaches with an error rate of just 0.77%. Its advanced architecture, combining Bi-LSTM networks and attention mechanisms, allows it to capture intricate relationships between operational and environmental variables. This demonstrates the transformative potential of AI in maritime engineering. However, the reliance on vast amounts of high-quality data and the interpretability challenges inherent in AI models underscore the need for further research into improving transparency and robustness.

The findings underscore that the number of parameters considered is a critical determinant of model accuracy, balancing computational efficiency and predictive precision. While the semi-empirical model is suited for rapid estimations, the physical model offers interpretability, and the AI-based model excels in data-rich scenarios.

A limitation of this study is the lack of validation of the physical model 6-DOF predictions due to the absence of real-world 6-DOF motion records. Future research should integrate actual measurements and hybridize traditional and AI models to combine interpretability with predictive power, providing scalable solutions for maritime fuel efficiency optimization.

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