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AI-BASED SURROGATE MODEL FOR THE PREDICTION OF SHIP FUEL CONSUMPTION REFLECTING HYDROMETEOROLOGICAL CONDITIONS

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ABSTRACT

Accurate prediction of ship fuel consumption is essential for optimizing ship performance and minimizing environmental impact. This study presents the development and validation of an artificial intelligence (AI)-based surrogate model specifically designed to predict Ship Fuel Consumption (SFC) in the case of a bulk carrier. The surrogate model employs a cutting-edge approach by combining deep learning techniques, specifically incorporating attention mechanisms into Bidirectional Long Short-Term Memory (Bi-LSTM) networks. This advanced model leverages a rich and diverse dataset comprising crucial operational parameters, including ship navigation, ship operational conditions, engine operational status, and Metocean data, to achieve highly accurate predictions of SFC. The dataset used for training and validation is sourced directly from realistic bulk carrier operations, ensuring the relevance and practical applicability of the model. Extensive generalization tests were conducted to evaluate the performance of the developed surrogate model. The results indicate that the AI-based surrogate model achieves long-term high accuracy in predicting ship fuel consumption under varying operational conditions. The developed surrogate model may serve as a valuable tool for bulk carrier operators, offering insights into fuel efficiency improvements and enhancing the overall sustainability of ship operations.

Keywords: Ship fuel consumption, Artificial Intelligence, Deep learning method, Ship Systems

1. INTRODUCTION

Maritime transport, essential for over 80% of global cargo volume, plays a crucial role in global trade and economic growth [1]. However, in the face of the Paris Agreement's targets, the shipping industry, accounting for 2.89% of global anthropogenic emissions, faces the challenge of decarbonizing to reduce greenhouse gas emissions by 50% by 2050 as compared to 2008 levels [2].

Weather routing is a strategy used in maritime operations to reduce SFC and GHG emissions. By optimizing the ship route, it enables more efficient operations, leading to lower fuel use. The core of the weather routing tool is a ship performance evaluation model, which can be used to estimate SFC reflecting hydrometeorological conditions. Ship performance evaluation models focus on two main aspects, namely, (a) physics-based and (b) data-driven models.

Physics-based models are effective for approximating SFC, using methods like ship energy performance and ship resistance estimation models [3]. These models consider various factors like engine and propeller performance, ship motions, external forces, and hydrodynamic effects in both calm water and rough conditions [4], highlighting that the accuracy of these models in predicting SFC heavily depends on accurately assessing ship resistance, including both calm water resistance [5] and added resistance from environmental factors[6][7]. Physics-based models are useful for ship performance optimization at the early stage of ship design. Nevertheless, these models often underestimate the time-varying hydrometeorological conditions, resulting in limited accuracy in predicting SFC. This limitation arises because physics-based models may not capture the nonlinear relationship between ship operational conditions and SFC.

AI and big data technologies present promising solutions for addressing the complexities in capturing various factors and interactions in physics-based models SFC predictions. AI can unravel complex relationships between measured SFC and numerous influencing parameters such as navigational conditions, ship operational conditions, energy system conditions, and hydrometeorological conditions [9]. Recent reviews have highlighted the potential of machine learning and deep learning methods in this domain. Algorithms are categorized into supervised [9][10], and unsupervised machine learning methods [11][12], and deep neural network methods [13][14]. These approaches offer a sophisticated way to predict SFC by integrating a broad range of influential factors. Most of the methods have been employed to predict the SFC based on diverse data sources [15]. The results indicate that high-frequency data is meaningful for data-driven models' development. AI and big data models for predicting SFC may not be accurate in terms of incorporating complex or extreme operational conditions. Detailed problems may involve data overfitting and difficulties in managing the complexity of big data patterns.

This paper introduces a deep learning model for the development of an AI-based surrogate model, aimed at predicting SFC reflecting hydrometeorological conditions. The proposed model incorporates complex big data patterns, and a range of influencing factors, and employs a Bi-LSTM network with attention mechanisms. The method utilizes big data collected from real operations of a bulk carrier. After training and testing, the AI-based surrogate model can be used to estimate SFC in various operational conditions. It concludes that the developed approach holds significant potential for contributing to environmentally sustainable shipping operations, showcasing the potential applicability of advanced AI techniques in realistic scenarios.

2. METHODS

In this paper, a feature importance method, namely, the decision tree (DT) methodology, is employed to analyze extensive big data records, identifying, and selecting key influencing factors that may impact SFC (Step I). This process involves the use of a Bi-LSTM network with an attention mechanism (Step II). Once trained and tested, the resulting AI-based surrogate model is capable of estimating SFC across various operational conditions (Step III). The methodology is structured into three distinct steps, as illustrated in Figure 1, thus providing a systematic approach for integrating advanced AI techniques with big data analytics to enhance the prediction accuracy of SFC in real operations.

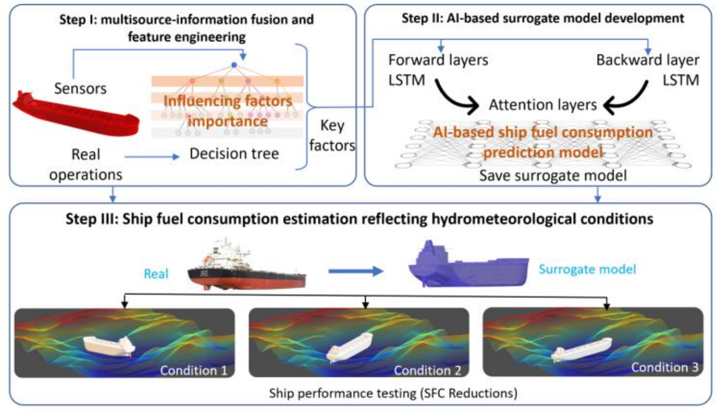

FIGURE 1: THE FLOWCHART OF THE DEVELOPMENT OF AN AI-BASED SURROGATE MODEL AND ITS APPLICATION.

2.1 Multisource-information fusion and feature engineering

The data collected sensors were installed on a bulk carrier, enabling the collection of extensive big data streams during operations, see Figure 2. This sophisticated hardware setup allowed for the measurement of 266 parameters. However, while this data collection system captures a wide and detailed range of time-domain parameters, not all are equally crucial for estimating SFC, nor do they contribute equally to the accuracy of model-derived results. Therefore, the development of a variable selection model was deemed necessary to effectively reduce data dimensions, ensuring that the most relevant parameters are considered in the analysis, thereby enhancing the precision and efficiency of the SFC prediction models.

The section employs a DT method to evaluate the significance of variables in relation to SFC, leveraging its hierarchical structure of nodes, branches, and leaves, as depicted in Figure 3. This method, recognized for its ability to unravel intricate relationships between input and output nodes, recursively divides datasets based on selected variables, potentially generating subsets of big data and forming decision rules, see Zhang et al., 2024 [16]. DTs can handle complex interactions and nonlinear relationships between variables by examining their splits and hierarchy. This approach is particularly effective due to its capacity to consider the importance of different variables, and it is advantageous for producing interpretable results.

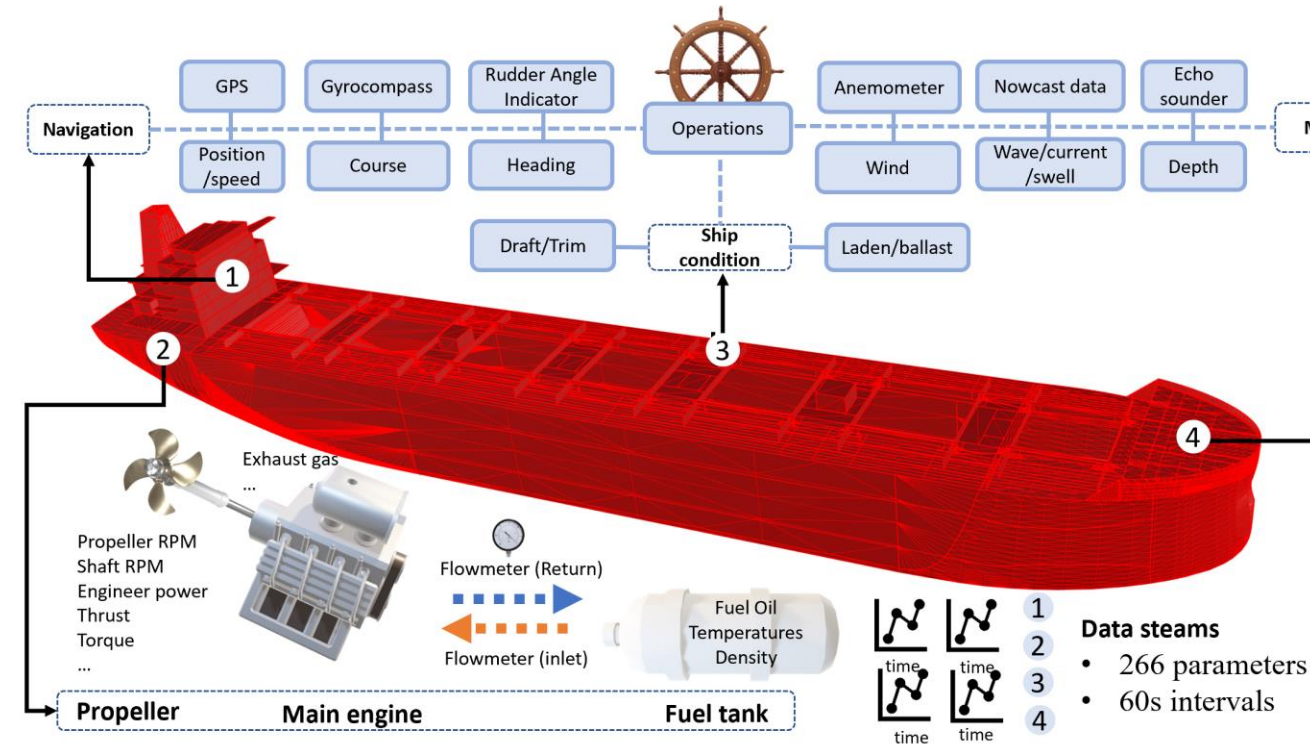

FIGURE 2: THE SENSORS AND THE DATA TYPES.

The DT model can analyze the complex interrelationships between various factors and assess their impact on SFC. The model evaluates the significance of different variables by considering aspects such as the frequency of their use in splitting the data and the resulting reduction in variance. This process helps to identify the importance of each variable. Variables with high importance values signify a strong influence on SFC, indicating that they play a significant role in determining or predicting SFC.

A crucial aspect of this approach is the selection of the top 'k' variables based on their ability to enhance prediction accuracy when used as inputs for the deep learning model (discussed in Section 2.2 of the paper). Interestingly, the analysis of the big data records suggested that altering the number of variables (either increasing or decreasing) could negatively affect the model's accuracy. Consequently, the selected top 'k' variables are used as inputs, see Figure 3. This selection and utilization of variables ensure the effectiveness and accuracy of the model in predicting SFC.

2.2 AI-based surrogate model development and validation

To develop an AI-based surrogate model, a deep learning method based on Bi-LSTM with an attention mechanism is adopted, see [8]. The architecture of the deep learning model is illustrated in Figure 4. The deep learning model incorporates both past and future dependencies and hence it can capture and utilize historical information efficiently. By considering past data trends and future operational scenarios, the model is designed to provide a comprehensive analysis of the SFC. The inclusion of attention mechanisms further enhances its capability by allowing it to focus on historical trends. This combination of predictive capabilities and focused data analysis positions the model as a potentially powerful tool for the accurate and efficient development of an AI-based surrogate model.

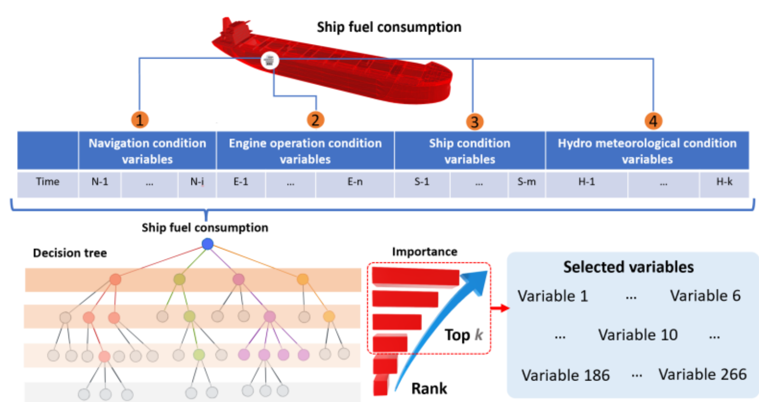

FIGURE 3: VARIABLES SELECTION USING DT.

Details of the deep learning model can be summarized with regard to the input layer, the Bi-LSTM layer, the attention mechanism, and the output layer as follows:

The input to the model incorporates essential variables analyzed through the DT model, as depicted in Figure 3. These chosen variables undergo pre-processing before being supplied to the following layers of the model.

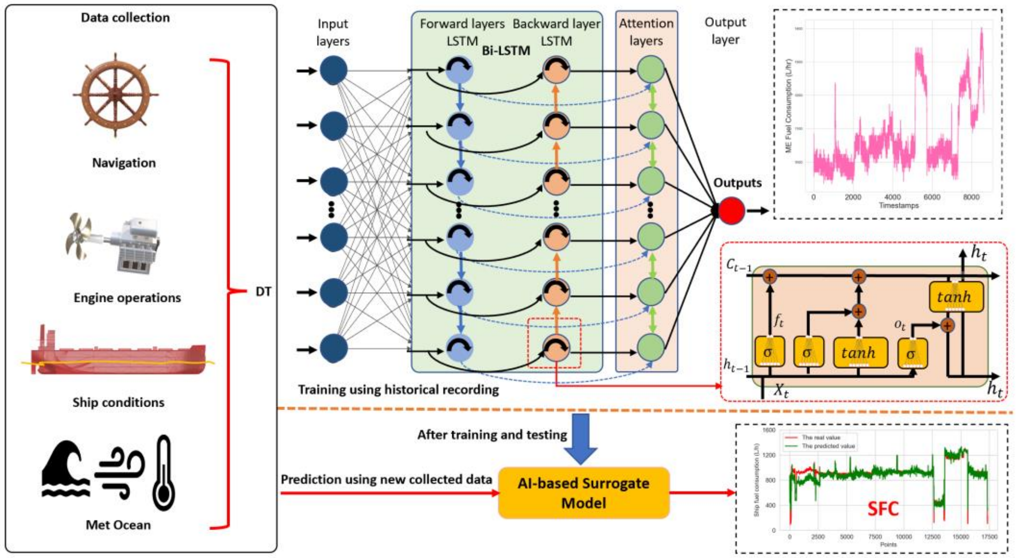

FIGURE 4: VARIABLES SELECTION USING DT.

The Bi-LSTM model described is composed of layers, each containing two LSTM sub-layers. Each LSTM unit within these layers has four interconnections that manage input and control signals (f_t, i_t, o_t) for the input, forget, and output gates, crucial for regulating memory storage, retention, and output. The model processes inputs at each time increment (x_t and h_{t-1}) using distinct weight vectors and an activation function to generate control signals for these gates (see red box in Figure 4). The mathematical framework of this process is detailed in Eqs (4-6), which describe the weight vectors (w), activation amounts (b), biases for different connection weights (b_f, b_i, and b_o), and the sigmoid activation function ($\sigma(\cdot)$). This structure enables the LSTM units to effectively handle time-series data, which is essential for the accurate prediction of SFC.

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \tag{1}$$
$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \tag{2}$$
$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \tag{3}$$

The state of a cell $\tilde{C}_t$ is presented as per Eq. (4). The value of the memory unit C_t is updated according to Eq. (5).

$$\tilde{C}_t = tanh(w_C[h_{t-1}, x_t] + b_c) \tag{4}$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

The output of hidden layer neurons h_t is defined as:

$$h_t = o_t * tanh(C_t) \tag{6}$$

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

To effectively predict SFC in the complex operational conditions of ships, deep learning models need to learn from both past and future data. Standard LSTM models only consider past information, but Bidirectional LSTM layers, as discussed by Zhang et al. (2024) [8], address this by including both forward and backward LSTM sublayers. This enables Bi-LSTM models to process information from both past and future time frames, thus capturing the intricate dynamics of ship systems more accurately and enhancing the precision of SFC predictions.

Forward sublayers process the input stream in a forward fashion, i.e., from the beginning t_b to the end t_e. The sublayers operate conversely to this (i.e., in a backward direction: from the end t_e to the beginning t_b). Given an input data stream $X = [x_1, x_2, \dots, x_n]$, a Bi-LSTM generates hidden states in both forward and backward directions as per Eqs. (7-8). Then, the hidden states from both directions are concatenated to obtain a comprehensive representation at each time step see Eq. (9).

$$\overrightarrow{h_t} = \text{LSTM}\,(x_t, \overrightarrow{h_{t-1}}) \tag{7}$$
$$\overleftarrow{h_t} = \text{LSTM}\,(x_t, \overleftarrow{h_{t-1}}) \tag{8}$$
$$h_t = [\overleftarrow{h_t}; \overrightarrow{h_t}] \tag{9}$$

where t represents the time step, and $\overrightarrow{h_t}$ is the hidden state in the forward direction. $\overleftarrow{h_t}$ is the hidden state in the backward direction, $[;]$ denotes the concatenation.

The attention mechanism in the model, as discussed by Zhang et al. (2023) [16], enhances its ability to handle input data streams by dynamically focusing on different parts and assigning varying importance to different time steps. This feature is particularly useful in emphasizing critical information and capturing extreme scenarios in the data. It operates by calculating attention scores and weights for each time step, based on the hidden representations from the Bi-LSTM layers, thereby improving the effectiveness in processing and interpreting the data. Given a specific time step t, the attention weight α_{tj} of other hidden layers for the current input of x_t is calculated as given in Eq. (10).

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

In the additive attention model, the attention score e_{tj} is calculated as specified in Eq. (11). In this equation, w_μ and w_w denote the weights of the fully connected layers involved in the model. Additionally, b_w represents the bias associated with different connection weights. These elements collectively contribute to the calculation of e_{tj}. Following this computation, the derived information is utilized to determine the attention weights, which are crucial for the functioning of the attention mechanism. This process is further detailed in reference [17].

$$e_{tj} = \quad w_{\mu}{}^{T} * tanh(w_w h_t + b_w) \tag{11}$$

The context vector c_t is defined as the weighted sum of the hidden states in the model, representing the attended information at a specific time step t. This concept is articulated in Eq. (12). Essentially, c_t captures the relevant information from different time steps, weighted according to their importance as determined by the attention mechanism. This process allows the model to focus on the most pertinent information at each time step, enhancing its predictive or analytical capabilities.

$$c_t = \sum_{j=1}^{n} \alpha_{tj} h_{tj} \tag{12}$$

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

$$SFC_t = softmax\,(w_c c_t + b_c) \tag{13}$$

In the above expression, w_c , and b_c are parameters (weight matrices or vectors) that are typically trained and determined during the process of model training.

The output layer of the model receives a context vector that is formulated as a weighted combination of hidden representations, which are generated from the attention mechanism process. This context vector is designed to effectively capture the most relevant information from the input data stream. By focusing on key elements that are crucial for the specific prediction task at hand, the context vector enables the model to make more accurate and relevant predictions. This method of selectively concentrating on the most important parts of the input data is a fundamental aspect of the attention mechanism, enhancing the overall performance and accuracy in predictive analysis. The output layer then processes these context vectors to predict SFC for each specific time step, making use of the concentrated and relevant information provided by the context vector to enhance the accuracy and relevance of its predictions.

To assess the accuracy and calculate the discrepancies between the actual and the predicted value, several statistical measures were employed: Root Mean Square Error (RMSE), Mean Square Error (MSE), the coefficient of determination (R^2 value), and error rates (e_n). These metrics were evaluated as outlined in Eqs. (14-17).

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

$$\text{MSE} = \frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n)^2 \tag{15}$$

$$e_n = (y_n - \hat{y}_n)/(y_n) \tag{16}$$

$$R^2 = 1 - \sum_{n=1}^{N}(y_n - \hat{y}_n)^2 \,/\, \sum_{n=1}^{N}(y_n - \bar{y}_n)^2 \tag{17}$$

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

2.3 SFC estimation in real conditions

The ship performance models presented in this paper are categorized into two types namely empirical and semi-empirical. They serve to estimate calm water resistance and additional resistance due to wind and waves[18]. Subsequently, these models are applied in testing ship performance during the design phase [7] and in operational route planning [19]. Therefore, these models are often used to develop surrogate models in ship design and routing. However, they are often time-consuming and underestimate the influence of time-varying hydrometeorological conditions. This section introduces the utilization of pre-trained models for the prediction of SFC aiming to enhance the precision and efficiency of future weather routing systems.

In Sections 2.1 and 2.2, the focus is on collecting historical data related to ship performance, weather, sea conditions, and navigational routes and determining key influencing features. A key aspect involves evaluating the predictions against actual ship performance to ensure accuracy. The results indicate that the effectiveness of the AI-based surrogate model hinges on its ability to accurately represent the nonlinear relationship between hydrometeorological conditions and SFC. Therefore, the AI-based surrogate model, is presented as an 'out-of-the-box' tool, see Figure 5. Such a model may be suitable for integration into ship navigation systems, bringing forth benefits such as improved prediction of fuel efficiency, enhanced safety, and optimized ship operations, see Section 3.3.

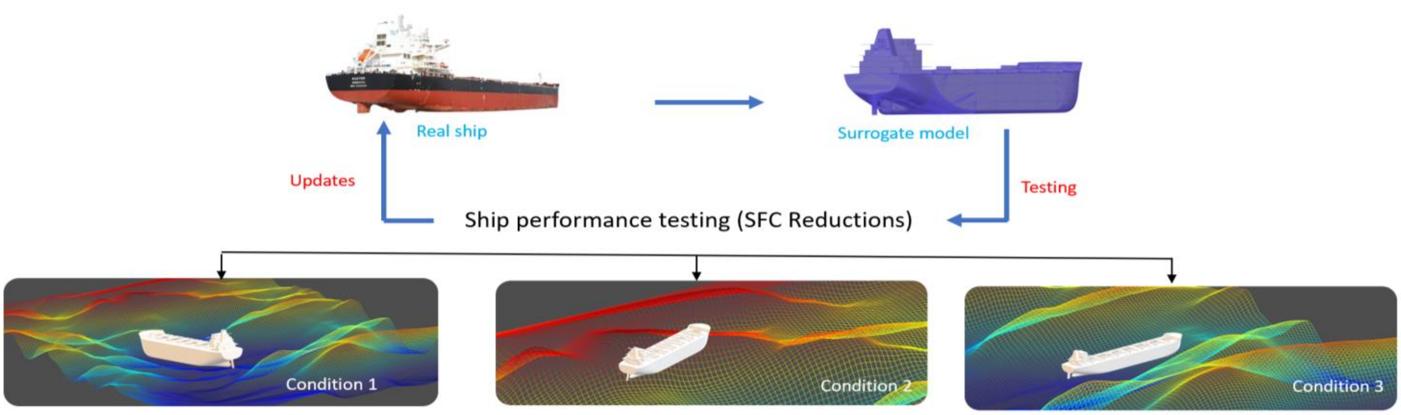

FIGURE 5: SHIP PERFORMANCE TESTING FOR WEATHER ROUTING USING AN AI-BASED SURROGATE MODEL.

3. CASE STUDIES

To validate the deep learning method for the development of an AI-based surrogate, the study utilized extensive big data records from real operations of a bulk carrier operated by Laskaridis Shipping Co. Ltd. This carrier has a deadweight tonnage (DWT) of 81,600.0 tons and dimensions of 229.0 meters in length and 32.0 meters in breadth. Figure 6 shows the voyages this ship undertook over a two-year period, from February 2021 to January 2023.

The dataset utilized for validation is extensive, consisting of over 1 million data entries, with each entry encompassing 266 parameters. This involved big data analytics techniques to gather information about ship navigation, engine performance, and operational conditions. A graphical depiction of these collected data instances is presented in Figure 7. The data was gathered at 60-second intervals, offering a comprehensive and detailed dataset for the thorough assessment and validation of the deep learning methodology.

The dataset used for this validation is substantial, comprising over 1 million data records, with each record containing 266 parameters. Big data analytics involved acquiring information on ship navigation, engine, and ship operational conditions as well as Metocean data, and a visual representation of the collected data instances is given in Figure 7. Data was collected at an interval of 60 seconds, providing a rich and detailed dataset for the evaluation and validation of the deep learning approach.

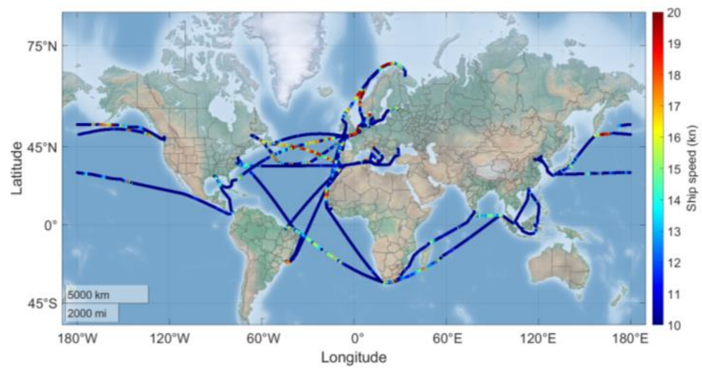

FIGURE 6: SHIP TRAJECTORIES OF SHIP OPERATION AT SEA OF A BULK CARRIER (February 2021 – January 2023).

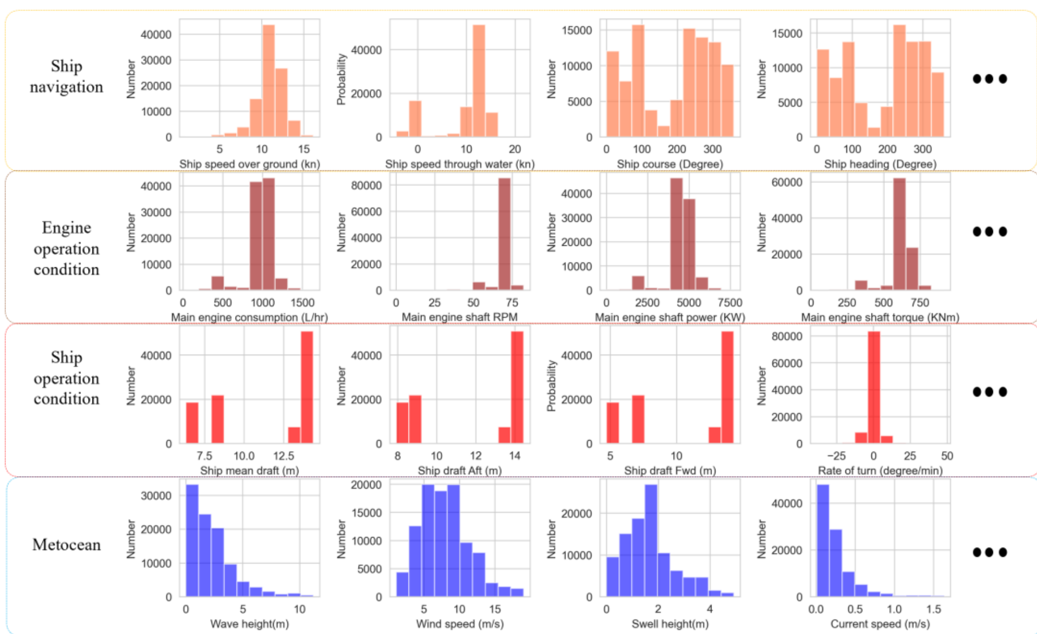

FIGURE 7: VISUAL REPRESENTATION OF THE COLLECTED DATA SAMPLES.

3.1 key variables selection using DT

Addressing the challenge of pinpointing key factors and excluding irrelevant data, the study implemented the DT regression method as detailed in Section 2.1. This method considered 266 variable sets, which included 265 parameters alongside SFC. The primary objective was to analyze time domain signals to derive significant insights into factors influencing SFC. For this purpose, 265 variables were categorized as the X database, while SFC was defined as the Y database. These X and Y databases were divided into training and testing sets, with the training set comprising 80% of the total data streams and the testing set making up the remaining 20%. To efficiently train the DT model, these substantial data sets were normalized. Further details on this process can be found in Zhang et al. (2024) [8]. The optimization of the DT model, along with the analyzed dataset, facilitated the assessment of variable importance, as depicted in Figure 8. Based on the importance of these variables and practical requirements, key factors such as ship navigation information (including ship speed, course, and heading), ship operation condition information (like draft as well as trim), engine operation data (main engine shaft RPM, main engine temperature), and external operational conditions were identified as primary control parameters, as shown in Figure 9.

These parameters play a crucial role in managing the ship energy and navigation systems.

3.2 The development of AI bases surrogate for ship fuel consumption prediction

Utilizing the gathered data streams, as illustrated in Figure 2, a DT model was employed to categorize and pinpoint the primary influencing factors on SFC, as shown in Figure 8. In this phase of the study, a Bi-LSTM architecture, enhanced with an attention mechanism, was developed for the purpose of training AI-based surrogate models. This approach aimed to leverage the sequential nature of the data for more effective and insightful analysis. The process of the development of AI-based surrogates includes the training stage and testing stage, see Figure 9.

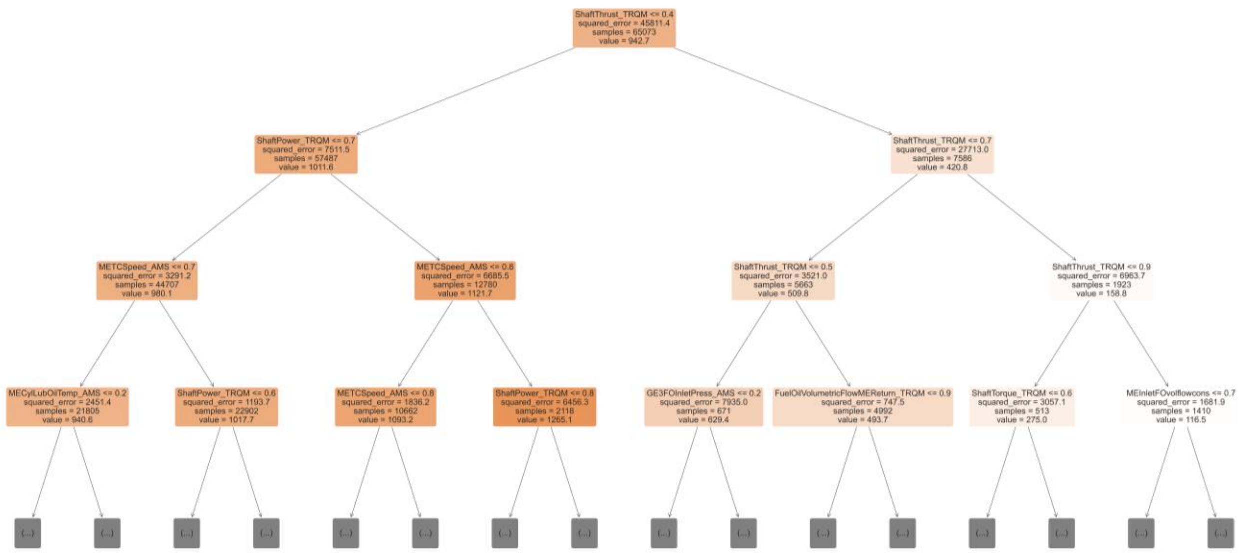

FIGURE 8: VISUALIZATION OF THE DT MODEL (THE FIRST FOUR LEVELS).

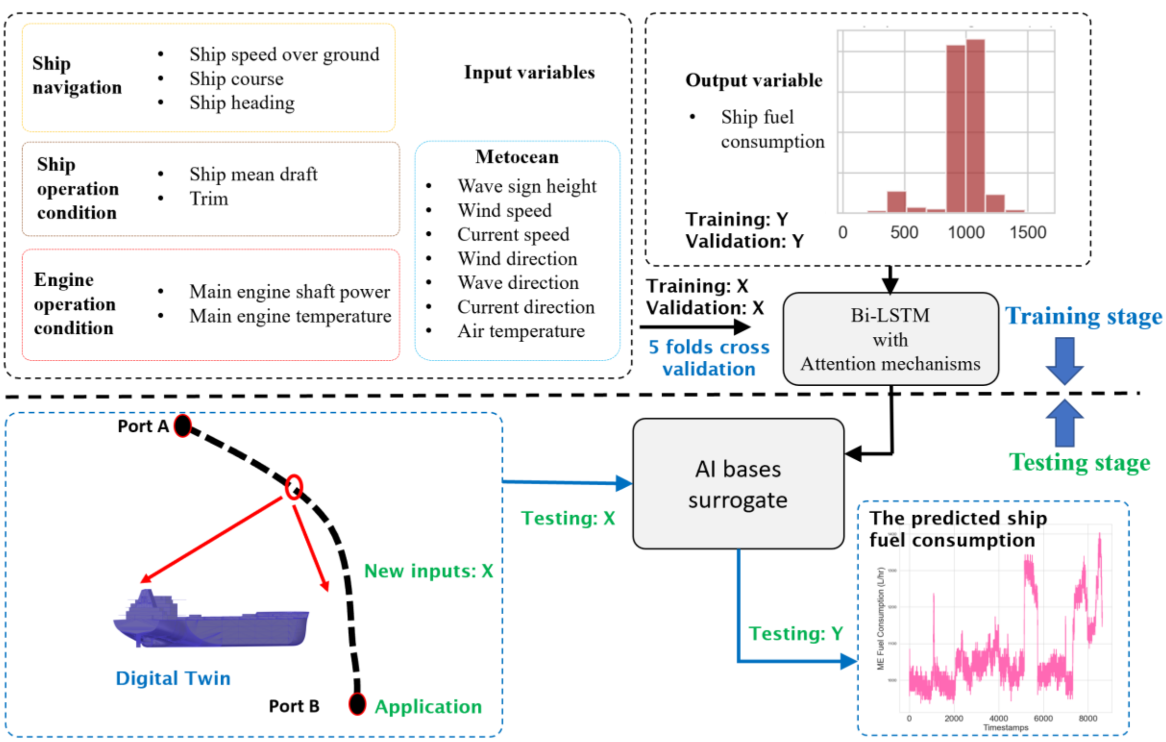

FIGURE 9: THE PROCESSING FOR TRAINING AND TESTING AI BASES SURROGATE.

The process of training, validation, and testing of a deep learning model for the development of an AI-based surrogate model is illustrated as follows:

(1) Model training and cross-validation

In training the deep learning model, the study implemented an architecture, as shown in Table 1. The optimal parameters were then identified based on achieving the lowest MSE during the validation process, as detailed in reference [16]. Details of the characteristics of the model and the chosen hyperparameters are concisely outlined in Table 1.

Training and validation losses were calculated using 80% of the dataset for training and 20% for validation, respectively. As shown in Figure 10, both training and validation losses decreased and eventually stabilized around the 178th epoch. This indicates that if no further improvement in validation performance is observed beyond this point, it would be prudent to terminate the training process early to prevent overfitting.

TABLE 1: THE PARAMETERS OF THE MODEL.

Model	Input variables	Output variable	Layers
Bi-LSTM with attention mechanisms	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

In this case study, after completing 178 epochs, the deep learning model reached a state of optimal fitting. This suggests a balanced convergence between the performance and the training data, indicating that the model is well-tuned to the data complexity without overfitting or being overly simplistic. The state of optimal fitting signifies that the model has achieved a desirable balance in capturing the intricacies of the big data without falling into the traps of overfitting or underfitting. Figure 10 also implies that the deep learning model can achieve an optimal fit by effectively mitigating both overfitting and underfitting. Furthermore, the MSE obtained through 5-fold cross-validation was reported as 2.04e-2, demonstrating the accuracy and efficacy of the model.

(2) Model testing

The deep learning model, once trained, was saved as an AI-based surrogate model specifically for predicting SFC. To ensure its broad applicability, this AI-based surrogate model underwent testing with extensive data streams derived from operational data. This test data corresponded to the period from February 2023 to June 2023, covering a total of 8 worldwide voyages, as depicted in Figure 11. Within this dataset, the voyages varied significantly in length, with the longest journey spanning 7223.9 nautical miles and the shortest covering 980 nautical miles. These details, including the distances of each voyage, are systematically presented in Table 2. Figure 11 demonstrates the use of the time-domain profile of the trained model to predict SFC across all the voyages. The differences between the actual and predicted SFC values were quantified using evaluation metrics such as the coefficient of determination (R^2, RMSE, MAE, and e_n). These results are detailed in Table 2 and illustrated in Figure 12. The analysis revealed that the R^2 values varied between 0.71 and 0.94 across different voyages. Specifically, Voyage 2 showed the most accurate predictions, with the smallest MAE recorded at 28.19 L/h and the lowest RMSE at 38.99 L/h. In terms of the average error rate e_n, which ranged from -0.51% to 5.56%.

These results affirm the viability of deploying the AI-based surrogate model as an efficient tool for forecasting SFC during comparable voyages, indicating that the AI-based surrogate model can capture the nonlinear relationship between hydrometeorological conditions and SFC in ship systems in real operational conditions. Consequently, the AI-based surrogate model can be out of box for evaluating the SFC in time-varying operational conditions.

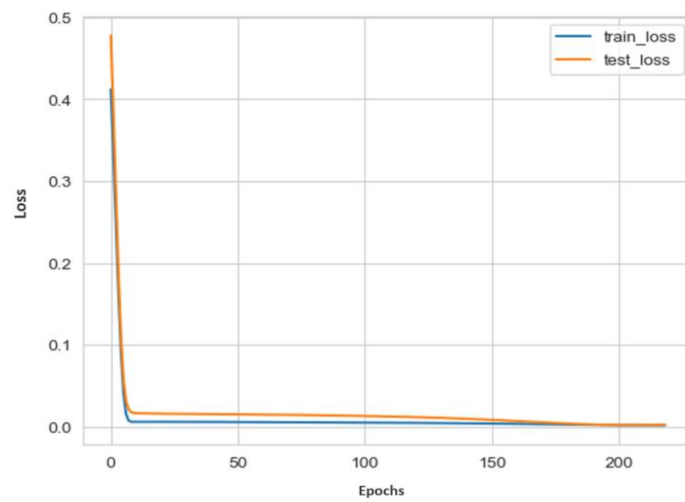

FIGURE 10: THE MODEL PERFORMANCE EVALUATION.

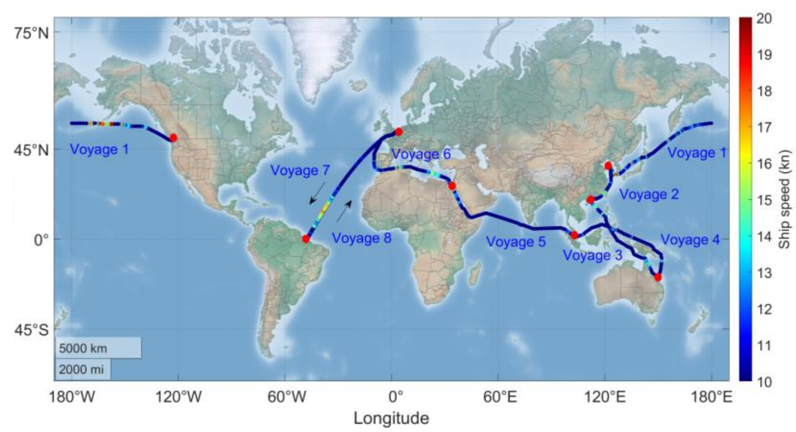

FIGURE 11: SFC PREDICTION FOR 8 GLOBAL VOYAGES USING THE AI-BASED SURROGATE MODEL.

TABLE 2: The Results Of GENERALIZATION ABILITY EVALUATION.

Voyage (V)	V 1	V 2	V 3	V 4	V 5	V 6	V 7	V 8
Lengths	7223.90 nm	980.22 nm	3035.639 nm	3764.36 nm	4724.23 nm	3954.41 nm	4230.67 nm	4197.65 nm
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
e_n	-0.51%	2.64%	-2.68%	5.56%	2.53%	1.36%	2.48%	-3.59%

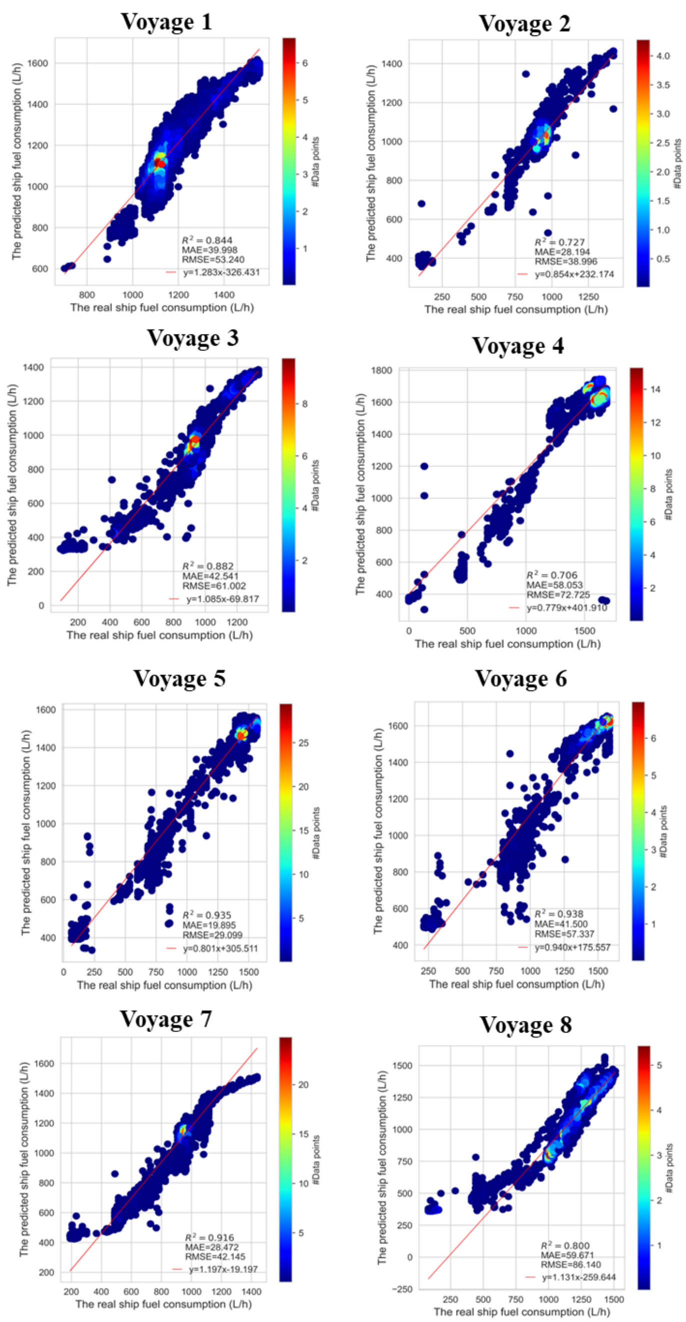

FIGURE 12: THE COMPARISONS.

3.3 Ship performance testing using an AI-based surrogate model

In this section, voyage 1 is used to carry out a case study and analyze the impact of the hydrometeorological conditions on SFC using an AI-based surrogate model.

(1) Ship performance testing in calm waters or in real operation. In this test, the hydrometeorological conditions (wave, wind, and current) are set to zero, indicating that the ship operates in calm waters. Subsequently, the SFC is estimated using the AI-based surrogate model. Figure 13 shows the predicted SFC in calm waters compared to the actual SFC in real operations. It reveals that operating the ship in calm waters can lead to a 7.27% reduction in SFC compared to real operational conditions.

(2) Ship performance testing against or following wind. In this test, an AI-based surrogate model is utilized to estimate the impact of wind on SFC. Three distinct data sets are created namely (a) a real wind model that maintains wind speed and direction while setting wave and current data to zero; (b) an against wind model that keeps the wind speed constant with direction against ship heading and setting current data to zero and (c) a following wind model that maintains the same wind speed with the direction following the ship heading, also with current data set to zero. Figure 14 illustrates that when the ship is following the wind, there is a 1.15% reduction in SFC as compared to when it is against the wind. Additionally, the SFC of the ship under actual wind conditions is higher than when following the wind but lower than when against the wind.

(3) Ship performance testing against or following wave

In this test, the setting for analyzing wave conditions mirrors the methodology used for wind. Three distinct scenarios are created: (a) keeping wave conditions consistent while nullifying wind and current data, to isolate wave impact on SFC; (b) setting wave direction against the ship heading with no current and no wind, to assess SFC in opposing wave conditions; and (c) aligning wave direction with the ship heading and eliminating current and wind data, to evaluate SFC with following waves.

Figure 15 illustrates that when the ship is following the wave, there is a 4.11% reduction in SFC as compared to the against wave scenario. Additionally, the SFC of the ship under actual wave conditions is higher than when following the wave but lower than when against the wave. This test, akin to the wind scenarios, serves to distinctly evaluate the influence of wave conditions on the ship's fuel efficiency and ship performance.

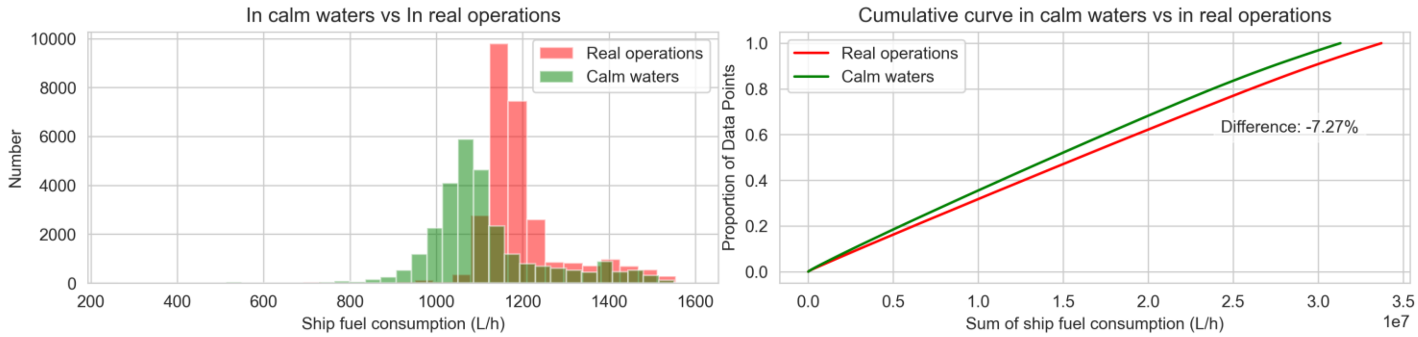

FIGURE 13: SFC IN CALM WATERS OR IN REAL OPERATIONS.

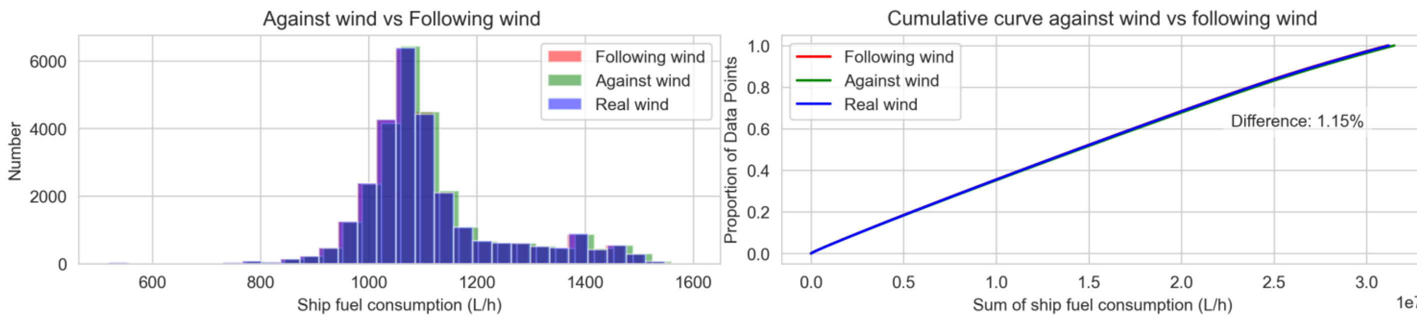

FIGURE 14: THE COMPARISON OF SFC AGAINST OR FOLLOWING THE WIND.

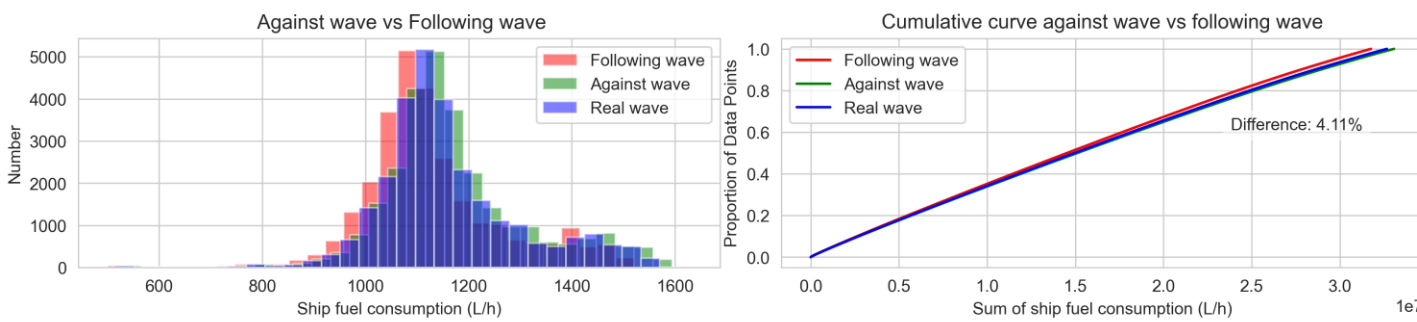

FIGURE 15: THE COMPARISON OF SFC AGAINST OR FOLLOWING THE WAVE.

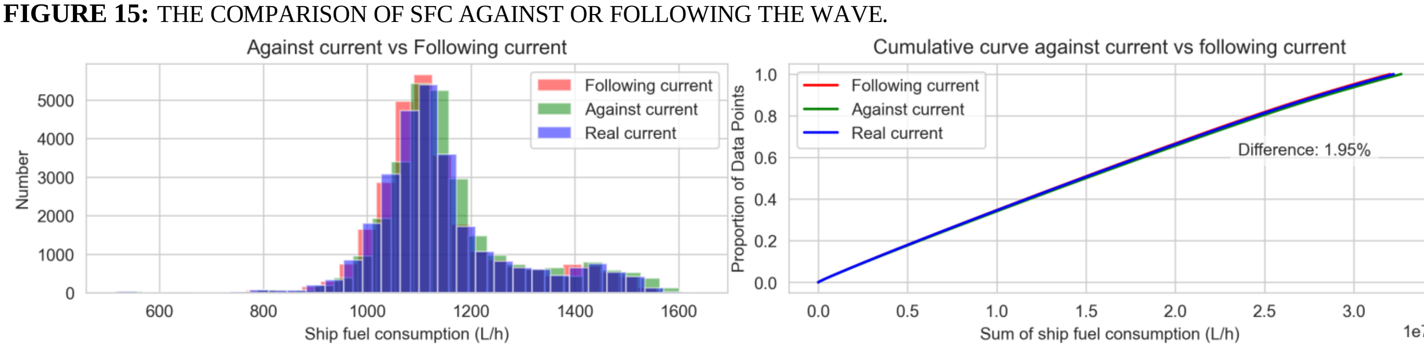

FIGURE 16: THE COMPARISON OF SFC AGAINST OR FOLLOWING THE CURRENT.

(4) Ship performance testing against or following current

In the current testing phase, the methodology parallels those used for wind and wave conditions, aiming to understand the impact of current on SFC. This involves three key scenarios: (a) Real current: maintaining constant current conditions while eliminating wind and wave effects to isolate the current impact on SFC; (b) Against current: directing the current against the ship heading and nullifying wind and wave data, to assess the SFC when facing opposing currents; and (c) Following current: aligning the current with the ship heading, with wind and wave influences removed, to evaluate the SFC benefits in following current conditions.

Figure 16 illustrates that when the ship is following the current, there is a 1.95% reduction in SFC compared to when it is against the current. Additionally, the SFC of the ship under actual current conditions is higher than when following the current but lower than when against the current.

The study assumes uniformity in the ship energy system and maintains a consistent speed throughout the various scenarios. These results underscore the effectiveness of the AI-based surrogate model in comprehending how hydrometeorological conditions affect SFC. Additional testing across various scenarios is required for further validation in future studies.

4. CONCLUSIONS

The paper presents a deep learning approach that utilizes an AI-based surrogate model using high-frequency data from ship operations. To validate this method, extensive data records spanning over two years of a Kamsarmax bulk carrier were utilized. The innovative application of a data-driven method combining DT and Bi-LSTM models with an attention mechanism for time-domain SFC prediction is promising. The Bi-LSTM model, enhanced with attention mechanisms, is particularly effective for developing an AI-based surrogate model to predict SFC. This is because it captures the characteristics of the ship energy system while considering real operational conditions over extended periods. The developed AI-based surrogate model estimates the impact of hydrometeorological conditions on SFC, and the results align well with real-world scenarios. The results show that, for voyage 1, dynamic hydrometeorological conditions lead to a 7.27% increase in SFC compared to calm water conditions, with waves, wind, and currents each having a significant impact (See Figures 13-16). In the future, further validation case studies utilizing physics-based models will be used to inform and enhance the AI-based surrogate model.

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REFERENCES

[1] UNCTAD, (2022). Review of Maritime Transport 2022.
[2] IMO, (2020 a). Fourth Greenhouse Gas Study 2020.
[3] Lang, X., & Mao, W. (2020). A semi-empirical model for ship speed loss prediction at head sea and its validation by full-scale measurements. Ocean Engineering, 209, 107494.
[4] Saydam, A. Z., Küçüksu, G. N., İnsel, M., & Gökçay, S. (2022). Uncertainty quantification of self-propulsion analyses with RANS-CFD and comparison with full-scale ship trials. Brodogradnja: Teorija i praksa brodogradnje i pomorske tehnike, 73(4), 107-129.
[5] Molland, A. F., Turnock, S. R., & Hudson, D. A. (2017). Ship resistance and propulsion. Cambridge university press.
[6] Vinayak, P. P., Prabu, C. S. K., Vishwanath, N., & Prakash, S. O. (2021). Numerical simulation of ship navigation in rough seas based on ECMWF data. Brodogradnja: Teorija i praksa brodogradnje i pomorske tehnike, 72(1), 19-58.
[7] Liu, S., and Papanikolaou, A. (2020). Regression analysis of experimental data for added resistance in waves of arbitrary heading and development of a semi- empirical formula. Ocean Engineering, 206.
[8] Zhang, M., Tsoulakos, N., Kujala, P., & Hirdaris, S. (2024). A deep learning method for the prediction of ship fuel consumption in real operational conditions. Engineering Applications of Artificial Intelligence, 130, 107425.
[9] Bocchetti, D., Lepore, A., Palumbo, B., & Vitiello, L. (2013). A statistical control of the ship fuel consumption. In Proceedings, international conference on the design, construction and operation of passenger ships, royal institution of naval architects, November (pp. 20-21).
[10] Coraddu, A., Oneto, L., Baldi, F., & Anguita, D. (2017). Vessels fuel consumption forecast and trim optimisation: a data analytics perspective. Ocean Engineering, 130, 351-370.
[11] Hu, Z., Jin, Y., Hu, Q., Sen, S., Zhou, T., & Osman, M. T. (2019). Prediction of fuel consumption for enroute ship based on machine learning. IEEE Access, 7, 119497-119505.
[12] Jeon, M., Noh, Y., Shin, Y., Lim, O. K., Lee, I., & Cho, D. (2018). Prediction of ship fuel consumption by using an artificial neural network. Journal of Mechanical Science and Technology, 32, 5785-5796.
[13] Kim, Y. R., Jung, M., & Park, J. B. (2021). Development of a fuel consumption prediction model based on machine learning using ship in-service data. Journal of Marine Science and Engineering, 9(2), 137.
[14] Yuan, Z., Liu, J., Liu, Y., Zhang, Q., & Liu, R. W. (2020). A multi-task analysis and modelling paradigm using LSTM for multi-source monitoring data of inland vessels. Ocean Engineering, 213, 107604.
[15] Li, X., Du, Y., Chen, Y., Nguyen, S., Zhang, W., Schönborn, A., & Sun, Z. (2022). Data fusion and machine learning for ship fuel efficiency modeling: Part I–Voyage report data and meteorological data. Communications in Transportation Research, 2, 100074.
[16] Zhang, M., Kujala, P., Musharraf, M., Zhang, J., & Hirdaris, S. (2023). A machine learning method for the prediction of ship motion trajectories in real operational conditions. Ocean Engineering, 283, 114905.
[17] Chorowski, J. K., Bahdanau, D., Serdyuk, D., Cho, K., & Bengio, Y. (2015). Attention-based models for speech recognition. Advances in neural information processing systems, 28.
[18] Lang, X. (2023). Data-driven ship performance models--emphasis on energy efficiency and fatigue safety (Doctoral dissertation, Chalmers Tekniska Hogskola (Sweden)).
[19] Wang, H., Lang, X., & Mao, W. (2021). Voyage optimization combining genetic algorithm and dynamic programming for fuel/emissions reduction. Transportation Research Part D: Transport and Environment, 90, 102670.