A novel GA-LSTM-based prediction method of ship energy usage based on the characteristics analysis of operational data

Wang, Kai; Hua, Yu; Huang, Lianzhong; Guo, Xin; Liu, Xing; Ma, Zhongmin; Ma, Ranqi; Jiang, Xiaoli

DOI
10.1016/j.energy.2023.128910

Publication date
2023

Document Version
Final published version

Published in
Energy

Citation (APA)
Wang, K., Hua, Y., Huang, L., Guo, X., Liu, X., Ma, Z., Ma, R., & Jiang, X. (2023). A novel GA-LSTM-based prediction method of ship energy usage based on the characteristics analysis of operational data. *Energy*, *282*, Article 128910. https://doi.org/10.1016/j.energy.2023.128910

Energy 282 (2023) 128910

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

A novel GA-LSTM-based prediction method of ship energy usage based on the characteristics analysis of operational data

Kai Wang [a,*,1], Yu Hua [a,1], Lianzhong Huang [a,**], Xin Guo [a], Xing Liu [a], Zhongmin Ma [a], Ranqi Ma [a], Xiaoli Jiang [b]

[a] Marine Engineering College, Dalian Maritime University, Dalian, 116026, China
[b] Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Mekelweg 2, Delft, 2628 CD, Netherlands

ARTICLE INFO

Handling editor: X Ou

Keywords:
Ship energy efficiency
LSTM neural network
Genetic algorithm
Energy consumption prediction
Shipping decarbonization

ABSTRACT

Optimization of ship energy efficiency is an efficient measure to decrease fuel usage and emissions in the shipping industry. The accurate prediction model of ship energy usage is the basis to achieve optimization of ship energy efficiency. This study investigates the sequential properties of the actual voyage data from a VLOC. On this basis, a model for predicting ship energy consumption is established by adopting a LSTM neural network that has better prediction performance for sequential datasets. To further enhance the performance of the established LSTM-based model, the network structures and hyperparameters are optimized by using Genetic Algorithm. Lastly, the application analysis is conducted to validate the established GA-LSTM-based model for ship fuel usage prediction. The established model for ship energy usage shows a significant improvement in prediction accuracy, compared to the original LSTM-based model. Meanwhile, the developed prediction model is more accurate than the existing BP, SVR, and ARIMA-based energy consumption models. The prediction errors for the ship's operational energy efficiency adopting the established GA-LSTM-based model can reach as low as 0.29%. Therefore, the established model can effectively predict the ship fuel usage under different conditions, which is essential for the optimization and improvement of ship energy efficiency.

1. Introduction

Water transport plays a critical role in promoting economic prosperity, because around 90% of worldwide trade is carried out via maritime transportation [1]. However, as much as 1.4 billion tons of CO_2 are released by the global shipping industry in 2020, making up nearly 6% of the total global CO_2 emissions. By 2050, yearly CO_2 emissions from shipping would account for 18% of the total world emissions if no actions are taken [2–4]. The IMO has continuously proposed indexes for assessing energy efficiency levels of ships, including the EEOI, EEXI, and CII, and also proposed some measures for improving energy efficiency, aiming to cut down CO_2 emissions [5–7].

The optimization of energy efficiency has been identified as a key measure to effectively mitigate carbon emissions from ships [47–49]. The improvement of ship energy efficiency is largely influenced by the forecast precision of the ship energy usage. Consequently, the accurate and well-performed model for ship fuel usage prediction is crucial to enhancing the ship's operational energy efficiency. The models for estimating ship fuel usage are frequently divided into two categories: artificial intelligence-based black box models and mechanism-based white box models [8–10]. Due to the high uncertainty of the influencing factors of ship energy consumption and the complexity of the navigational environments, the mechanism models based on the empirical formulae usually have low model accuracy and weak adaptability to variable navigation environments. The artificial intelligence technology promotes the progress of black box models based on big data learning. With big data on ship fuel consumption and navigation environment information, the prediction model of ship fuel usage adopting machine learning and intelligent algorithm based on the real ship operation data has shown certain advantages and has attracted extensive research and attention [11–13]. Pagoropoulos et al. [14] investigated ship performance evaluation by using a support vector machine

* Corresponding author.
** Corresponding author.
E-mail addresses: kwang@dlmu.edu.cn (K. Wang), huanglz@dlmu.edu.cn (L. Huang).
[1] These authors contributed equally to this work.

https://doi.org/10.1016/j.energy.2023.128910
Received 16 May 2023; Received in revised form 16 August 2023; Accepted 24 August 2023
Available online 26 August 2023

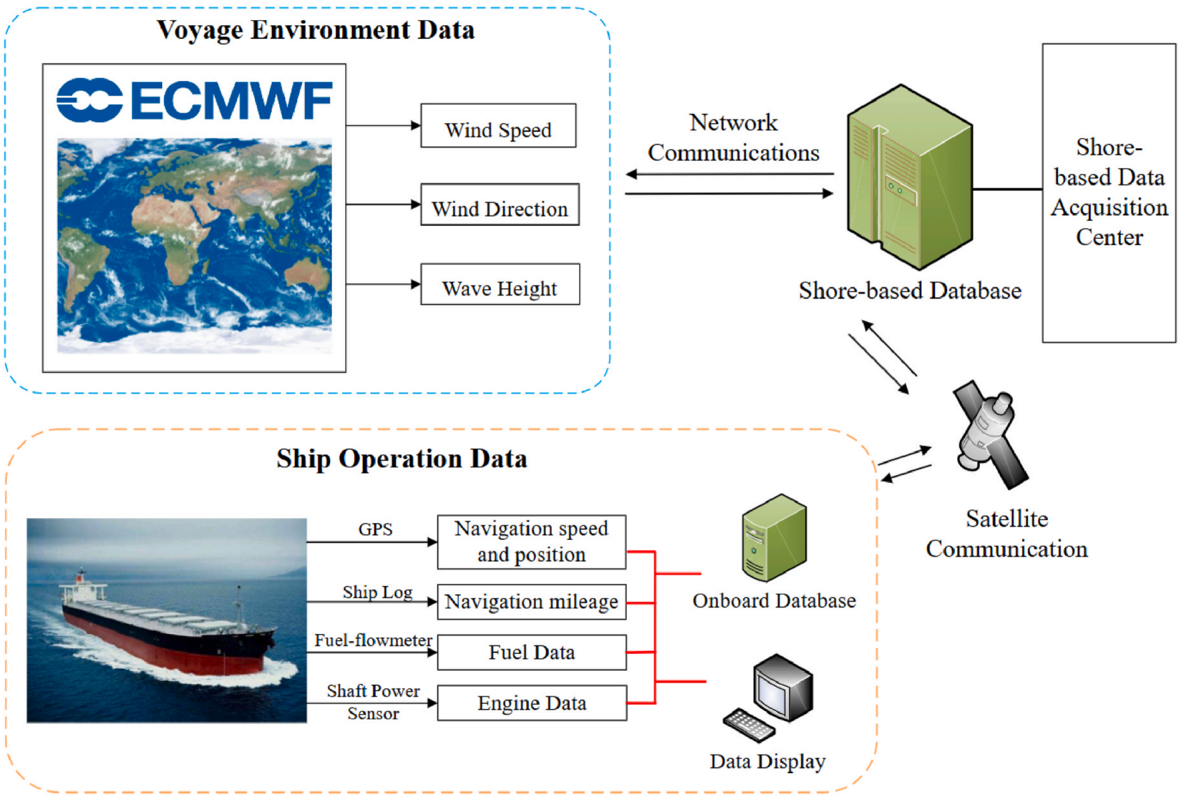


Fig. 1. The acquisition process of data related to ship fuel usage.

Table 1
The data acquisition methods.

Parameters	Sensor	Location	Diagram
Sailing speed and position	GPS	Bridge	
Navigation mileage	Ship log	Bridge	
Shaft power	Shaft power sensor	Main shaft	
Fuel consumption	Fuel-flowmeter	Fuel pipeline	

(SVM) and validated the proposed method through a study case analysis. Gkerekos et al. [15] employed the SVM, the random forest regressors (RFR), and the artificial neural network (ANN)-based models by using noon report data and the Automatic Data Logging & Monitoring system (ADLM), in order to achieve the prediction of ship main engine energy usage. Wang et al. [16] carried out feature screening and compression of ship energy consumption data by using Ridge Regression (RR) and the Least Absolute Shrinkage Selection Operator (LASSO), and then established an energy consumption prediction model. In addition, Hu et al. [17] developed a forecast model for ship energy usage through the emerging algorithm XGBoost based on the energy usage data. On this basis, Bayesian optimization was adopted to optimize its hyper-parameter value and a better prediction performance is obtained. Yang et al. [18] presented a grey box model for estimating ship energy consumption through adopting GA, which can effectively achieve the forecast of ship energy usage. Jeon et al. [19] developed a multilayer ANN-based model for predicting the energy usage of marine engines, and investigated the impact of various hidden layers, and neuronal density levels on the performance of the established forecast model. In

Table 2
The partly obtained data related to fuel usage of the ship.

Trim /(°)	Heel /(°)	Wind speed /(m/s)	Wind direction /(°)	Sailing speed /(kn)	Sailing direction /(°)	Wave height /(m)	Fuel consumption/(m^3/10 min)
−0.2	−0.1	1	58	11.9	38	0.820	0.39
−0.1	−0.1	0.5	93	11.7	36	0.817	0.37
−0.2	0	3.3	57	11.8	37	0.816	0.39
−0.2	0	2.5	357	11.6	37	0.818	0.40
−0.2	0	1.8	348	11.7	38	0.822	0.44
−0.1	0	3.4	0	11.9	37	0.830	0.47
0	0	3.5	277	11.9	38	0.839	0.51
…	…	…	…	…	…	…	…
−0.2	−0.1	4.3	340	12.2	38	0.859	0.37
−0.4	0	1.8	357	12.3	38	0.877	0.39
−0.3	0	1.3	15	11.8	37	0.894	0.38

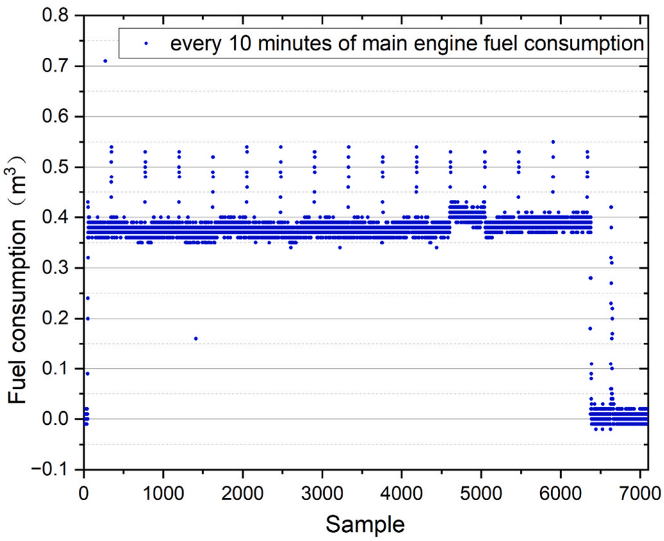


Fig. 2. The sequential distribution characteristics of ship fuel consumption.

addition, the multilayer perceptron (MLP) was utilized to achieve the ship propulsion power prediction by integrating the AIS, ship performance, and meteorological data [20].

The continuously collected large amount of ship energy consumption data gives a wealth of information for the development of the prediction model. In dealing with large samples and multi-dimensional data, the adoption of neural network technology has more advantages for the prediction models establishment. A well-performed prediction model of ship fuel usage was successfully created by using an ANN to learn noon report data, which confirmed the viability of developing the fuel usage model by learning the real operational data [21]. Hu et al. [22] established the energy consumption model by using the ANN and Gaussian process regression, and compared the effectiveness of the prediction models. The findings of the experiment demonstrated that the fuel usage of ships is obviously affected by the maritime environment. To effectively predict the ship energy consumption considering multiple influencing factors, Yan et al. [23] investigated a BP-based ship energy efficiency model. Additionally, Shen et al. [24] proposed a Deep Belief Network (DBN)-based ship energy consumption prediction model by taking into account diverse marine meteorological circumstances, which can dynamically forecast ship fuel usage under time-varying sea environments. The Convolutional Neural Networks (CNNs) were also used to assess ship performance based on the navigation data from a sizable shipping database [25]. Moreover, Wang et al. [26] proposed to forecast short-distance operational circumstances of cruise ships through the wavelet transform neural network, and established an optimization model of ship fuel usage to ensure the ship running at the optimal state when encountering various working conditions, thus to reduce the amount of fuel usage. Lee et al. [27] adopted a deep feed-forward neural network (DFN) to develop a model for ship power prediction by learning the navigational environment information and ship operation data. The established DFN-based model shows better prediction performance when compared to the MLR and SVR-based models. Alonso et al. [28] established a diesel engine emission prediction model by adopting ANN neural network. On this basis, the genetic algorithm (GA) is used to optimize the settings of diesel engine parameters according to the

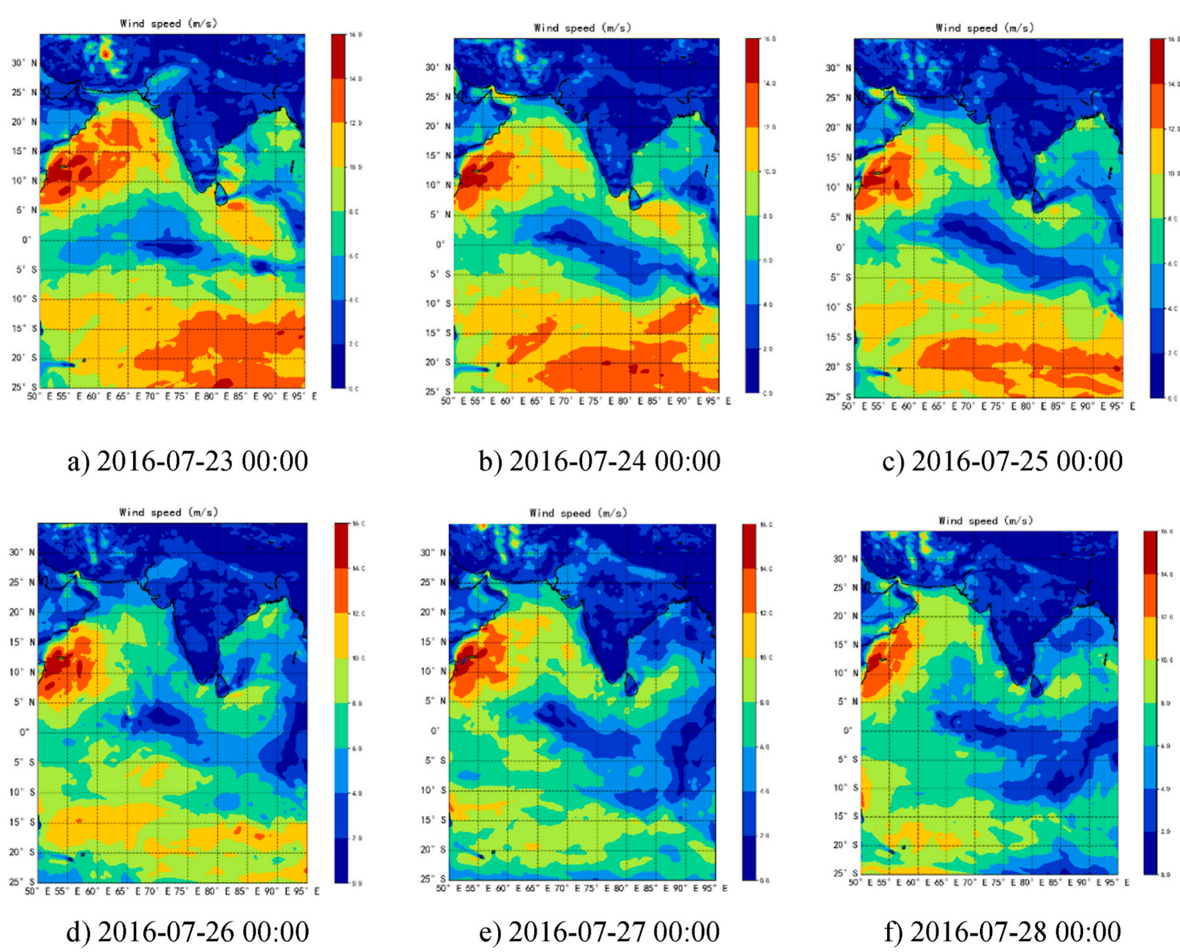


Fig. 3. The spatiotemporal distribution characteristics of wind speeds.

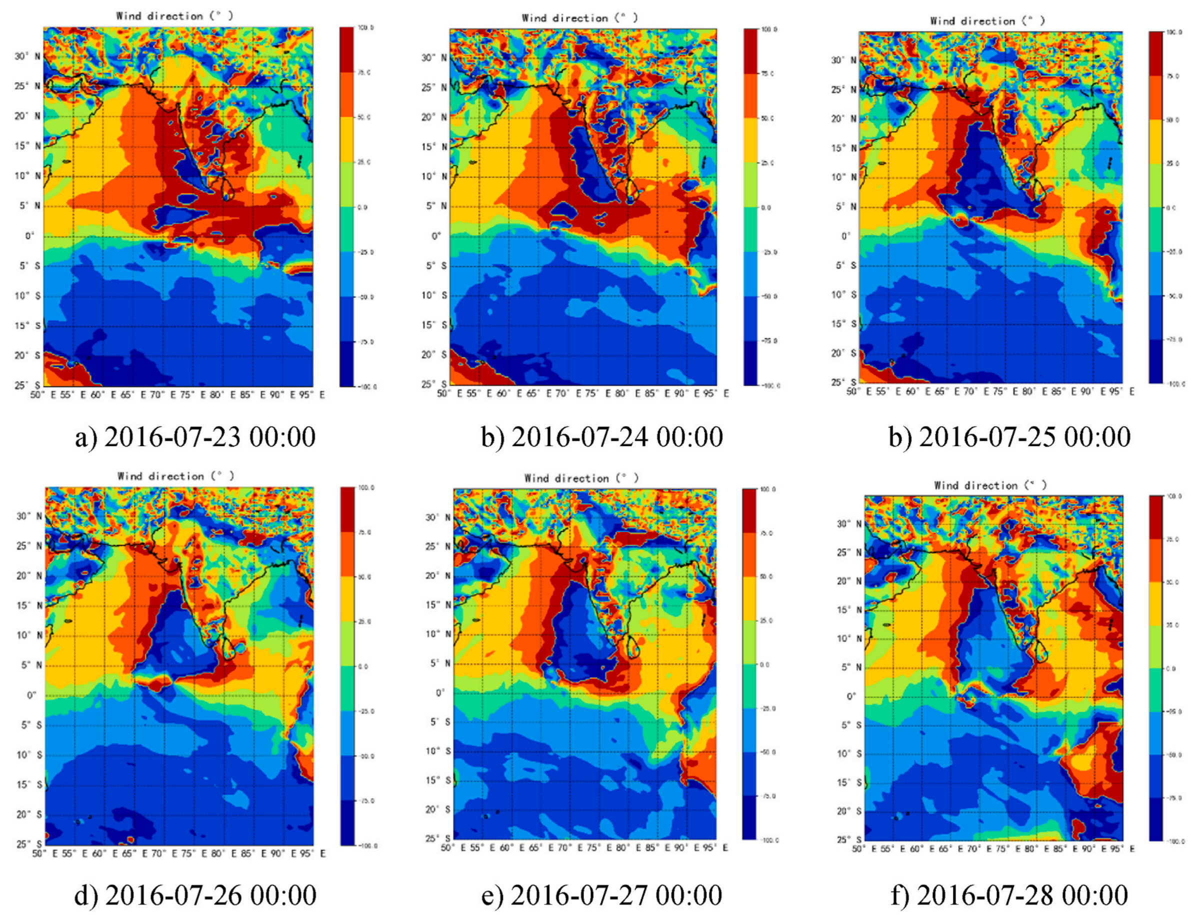


Fig. 4. The spatiotemporal distribution characteristics of wind directions.

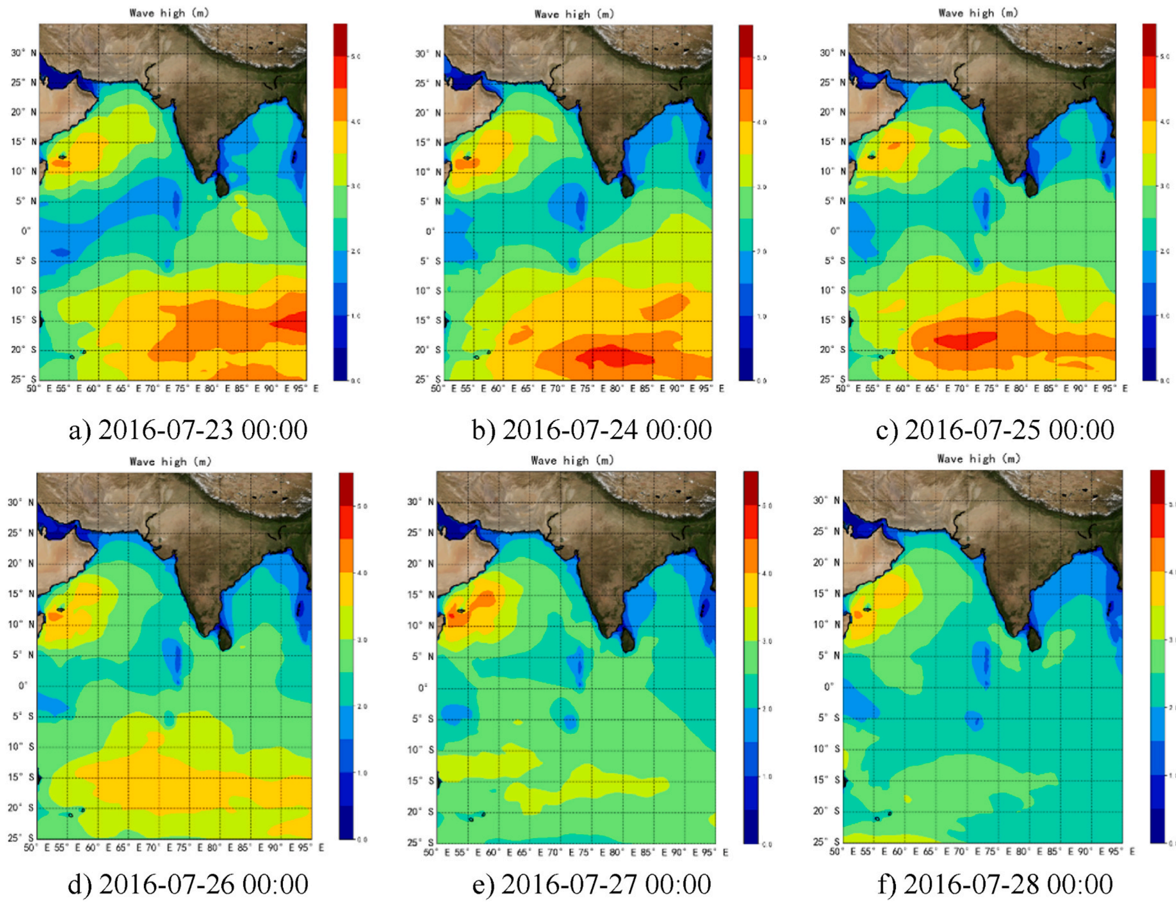


Fig. 5. The spatiotemporal distribution characteristics of wave heights.

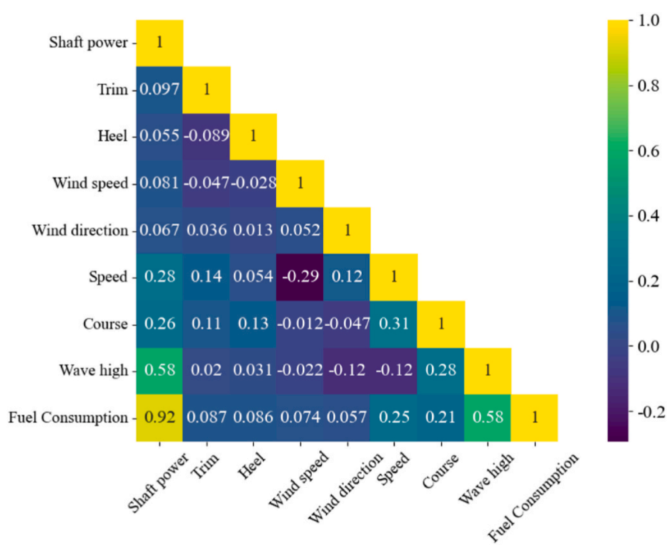


Fig. 6. The correlation analysis of the parameters related to ship fuel consumption.

prediction results of the ANN model to reduce the fuel consumption and emissions of the diesel engine.

Despite extensive research on the prediction of fuel consumption, it is still a challenge to achieve accurate prediction of ship fuel consumption due to the reasons: a) the ship is a complex big system and the energy consumption is influenced by multiple dynamic factors; b) those factors are usually complex and ever-changing, and has obvious sequential characteristics, making it hard to achieve accurate prediction of ship fuel consumption. To the best of our knowledge, there is still a lack of methods that has strong power for learning the complex ship energy consumption data with obvious sequential characteristics. The precision of the energy usage prediction model needs to be further enhanced. To close this research gap, we propose to the LSTM, which can solve the difficulty of predicting sequential data and can reflect influence of the previous input data on the latter input data, to achieve accurate prediction of ship energy consumption. LSTM is one particular kind of RNN, which is proposed to solve the difficulty of predicting sequential data and can reflect influence of the previous input data on the latter input data. LSTM has widespread applications in ship trajectory, navigational environment, and energy consumption prediction [29–31]. Yuan et al. [32] proposed a method for dynamical forecast of fuel consumption rate of the ship by adopting the LSTM network, which considers effects of navigational state and environments including water depth, wind speed, and wind direction. The experimental results demonstrated that the established model performs better than the regression-based models and the RNNs-based models. Zhu et al. [33] also developed a forecast model of ship fuel usage by using the LSTM-based method. The study results demonstrated that the precision of the established prediction model can be increased by 11.8% when compared to the traditional ANNs-based model. However, the structures and parameter settings of the LSTM-based model have a certain influence on the prediction performance when establishing the LSTM-based energy consumption model [34–36]. Therefore, selecting the optimal parameters is of great significance to enhance the forecast performance and generalization ability of the LSTM-based prediction model. The hyperparameter settings and network structure selection in the previous

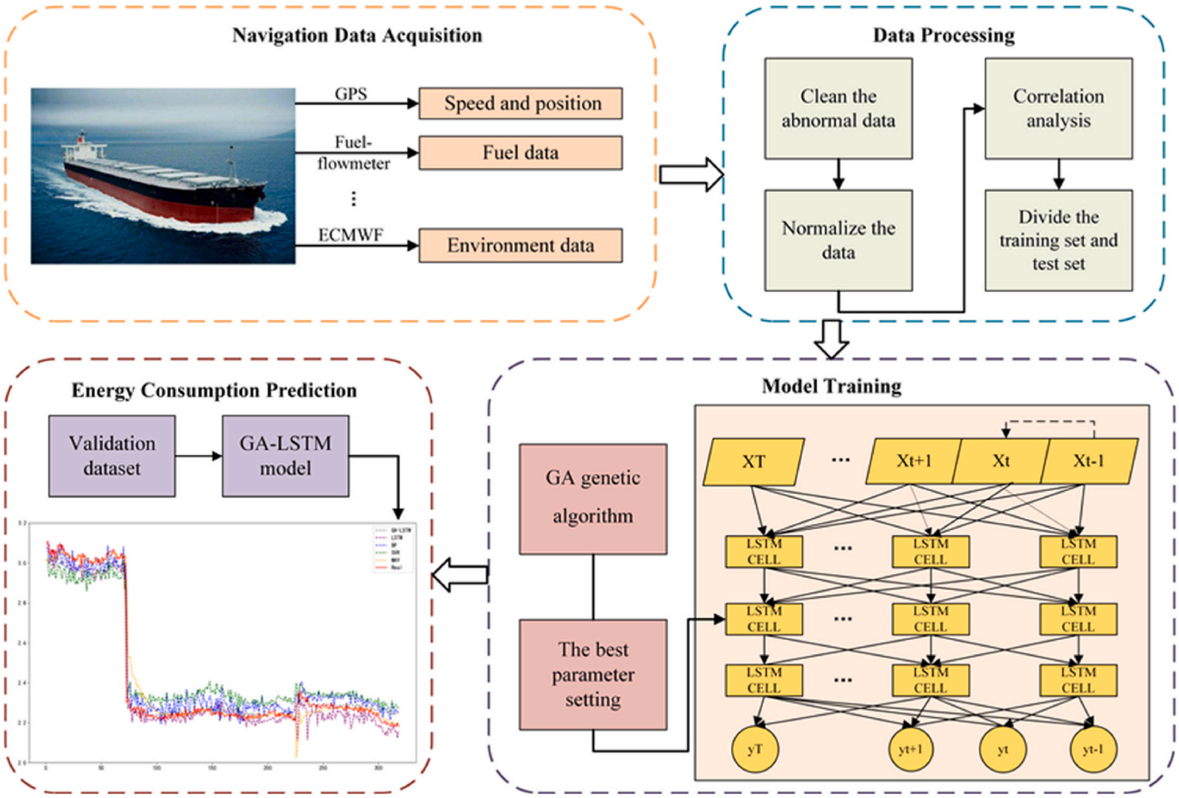


Fig. 7. The framework of the GA-LSTM-based model for ship fuel usage forecast.

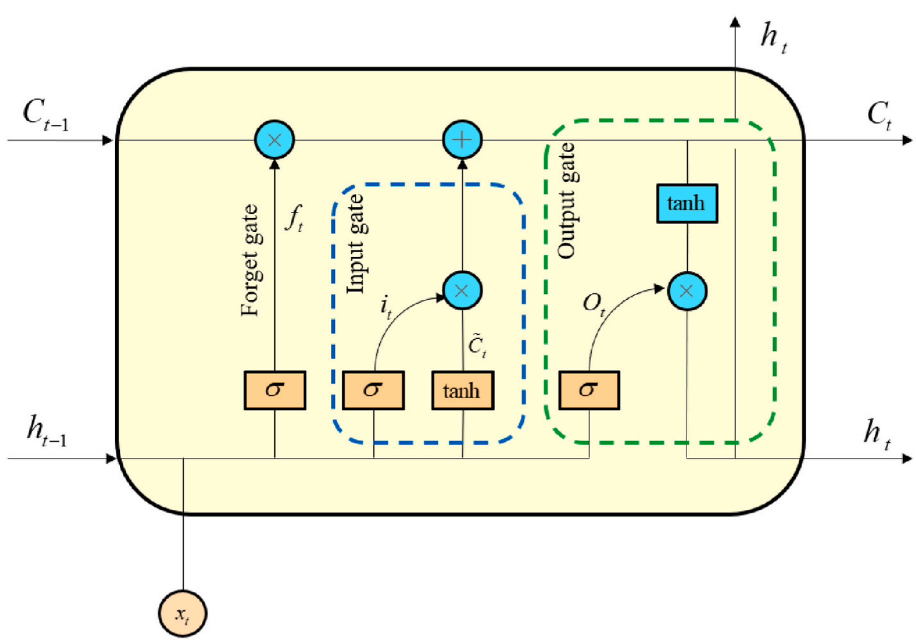


Fig. 8. The cell logic structure of the LSTM network.

studies are mainly based on empirical trial-and-error, which would weaken the forecast performance of the LSTM-based model for ship fuel usage prediction. In recent years, some researchers have tried to adopt different optimization algorithms for hyperparameter selection, among which the genetic algorithm (GA) has the advantages of strong merit-seeking ability and easy implementation, and has been widely used in the optimization of neural networks and has achieved good optimization results [37, 38]. Therefore, a forecast method for the ship energy usage based on the LSTM neural network with hyperparameters (such as the number of neural network lays, the number of neurons per layers, and the number of samples passed to the program for training in a single pass Batch_size) and network structure optimized by GA is investigated, to further enhance the forecast performance and generalization ability of the ship energy consumption model.

In summary, the main innovations and contributions of this research work mainly include: 1) A LSTM network, which is more suitable for

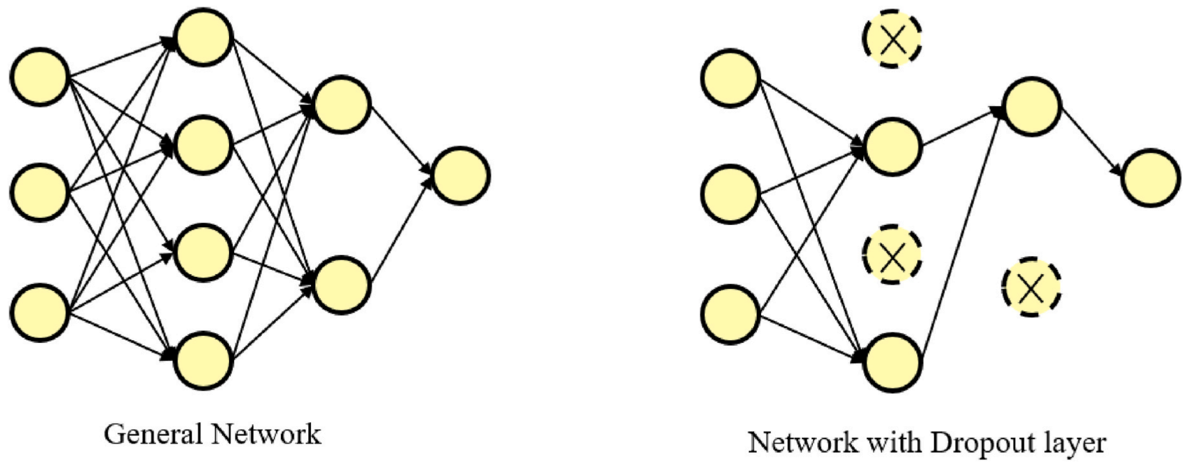


Fig. 9. Working schematic of the Dropout layer.

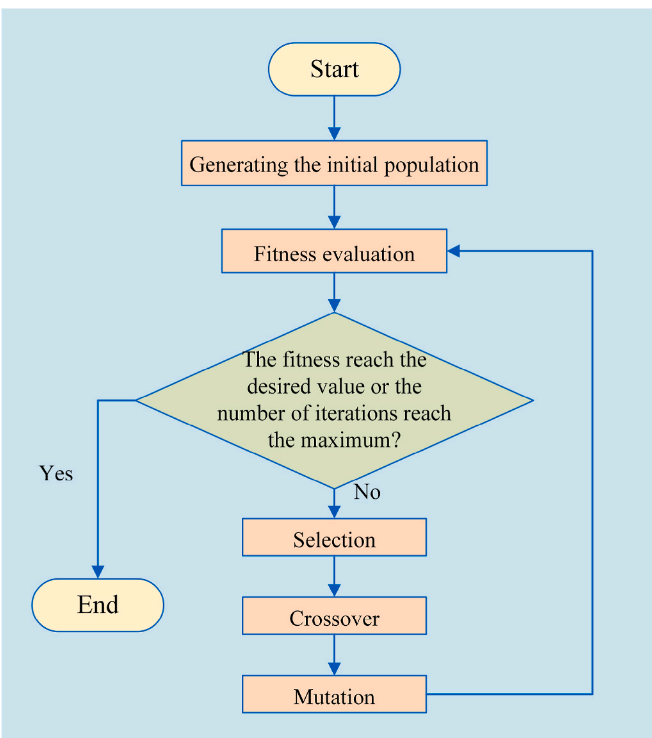


Fig. 10. The implementation processes of the GA algorithm.

dealing with sequential datasets related to ship fuel usage, is utilized to develop the model for predicting ship fuel consumption; 2) The GA is proposed to tune the parameters and structures of the LSTM neural network in terms of the number of network layers and neurons, and finally a GA-LSTM-based energy consumption prediction model is developed according to the GA optimization results. The established GA-LSTM-based energy consumption model, which fully considers the influence of parameters including ship trim, heel, navigational environments, and sailing speed, shows a better performance than the BP, support vector regression, and ARIMA-based models that have been adopted for the fuel consumption prediction in the above-mentioned researches. The case study results show that the prediction error can be improved by up to 15.6% in terms of MSE for the GA-LSTM-based energy consumption model, when compared with the original LSTM neural network. The established GA-LSTM-based model can describe and predict the ship fuel usage under various conditions more accurately and rapidly than the existing methods, which is critical for fuel usage optimization and carbon emissions control, and thus contributing to the decarbonization of the shipping industry.

This paper's remaining parts are structured as follows: the data acquisition method and the voyage data characterization analysis are investigated in **Section 2**. Then, a GA-LSTM-based prediction model of ship energy consumption is built in **Section 3**. An application analysis of the established GA-LSTM-based fuel consumption prediction model, including the comparative analysis of different prediction algorithms and the prediction analysis of the ship's operational energy efficiency, is investigated in **Section 4**. Lastly, **Section 5** concludes the study and prospects future research work.

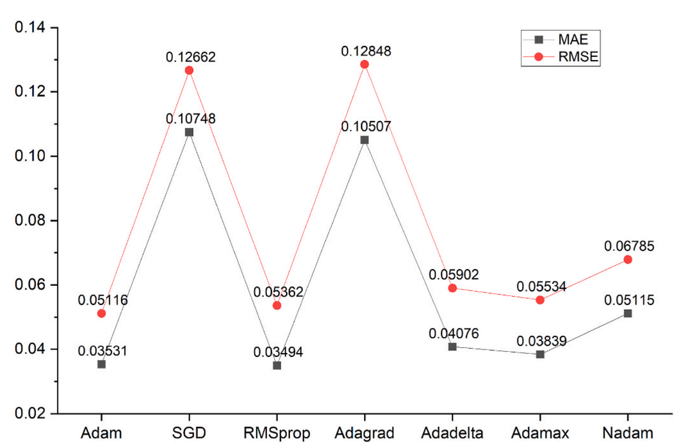


Fig. 11. Comparative analysis errors of different optimizers.

Table 3
Comparison of LSTM neural networks trained with different optimizers.

Items	Adam	SGD	RMSprop	Adagrad	Adadelta	Adamax	Nadam
MAE	0.0353	0.1075	0.0349	0.1051	0.0408	0.0384	0.0511
RMSE	0.0512	0.1266	0.0536	0.1285	0.0590	0.0553	0.0679

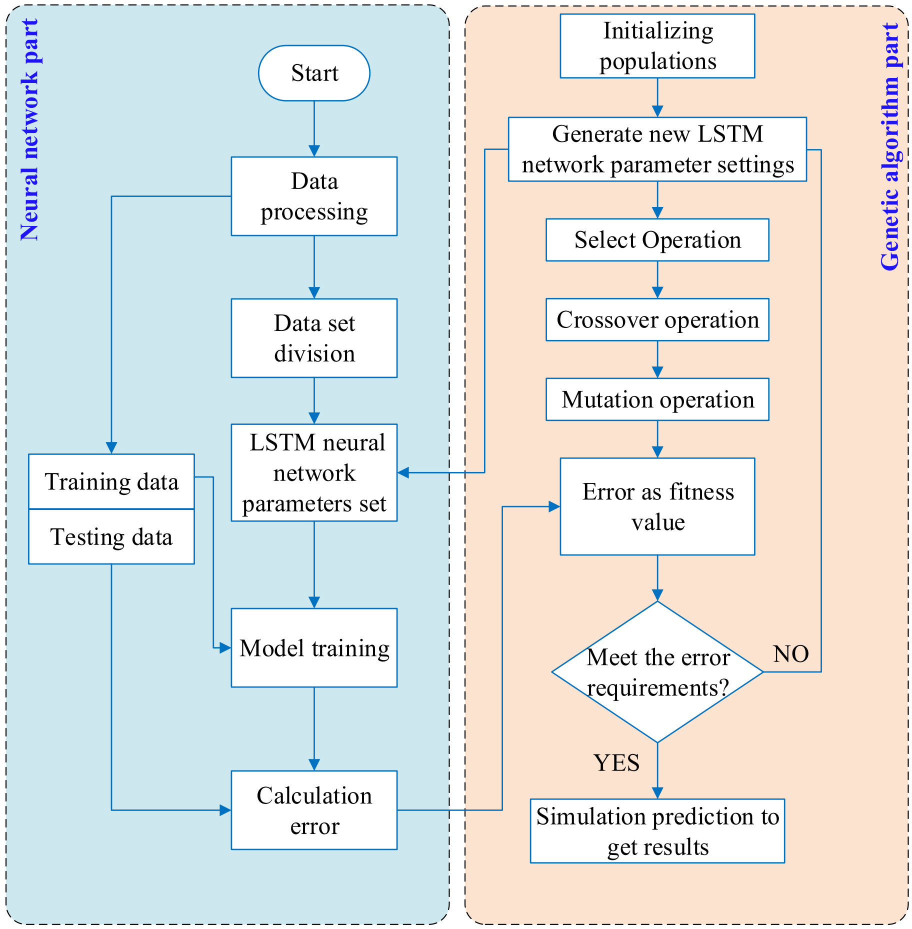


Fig. 12. The network training and optimization processes of the prediction model.

2. Acquisition and analysis of the data related to ship fuel usage

2.1. Data acquisition and pre-processing

The parameters influencing ship energy consumption include the ship's operational information (including ship trim, heel, sailing speed, and sailing route), and the navigational environment factors. The data acquisition system receives the related data through corresponding sensors, and then sends and stores them to the onboard database and the shore-based database. On this basis, the obtained data can be displayed through the onboard and shore-based energy consumption management system, as given in Fig. 1. In addition, the acquisition methods of data related to ship fuel usage are given in Table 1.

The data on the trim, heel, sailing speed, sailing route, and the marine main engine fuel consumption is obtained from the corresponding onboard sensors, while the navigational environment information is acquired from the European Centre for Medium-Range Weather Forecasts (ECMWF). The wind speed and wind direction is obtained though the vector operation based on the ECMWF environmental data. Based on the data analysis of trim, heel, navigational environments, sailing speed, sailing direction, wave height, as well as the marine engine fuel usage, the mapping relation between the amount of fuel usage and the multiple influencing factors can be analyzed. On this basis, the model for ship energy usage forecast can be established and the effective prediction and evaluation of ship fuel usage can be achieved.

Due to the different time scales for the collected fuel consumption data and the navigation environment data acquired from the meteorological center. It is necessary to conduct the data pre-processing. Firstly, daily 0:00 is taken as the data recording point, and every 10 min of main engine fuel consumption data was transformed into hourly ship fuel consumption data. Meanwhile, according to GPS data and the ECMWF environmental data, the cubic B-spline interpolation, which has good numerical computational performance and controllability [39], is utilized to make the frequency of meteorological and sea state data consistent with the frequency of data collected by the real ship. In addition, due to the abnormal values and noise in the collected data, the cleaning of the obtained data, including the processing of missing and abnormal navigation environment and ship energy consumption data caused by weather and equipment problems are conducted, to guarantee the precision of the established prediction model and the effectiveness of the fuel usage prediction analysis. After those data processes, the obtained data related to ship fuel usage is partly given in Table 2.

2.2. The characteristics analysis of the data related to ship fuel usage

To know well the distribution characteristics of ship energy consumption and then develop a more effective model for predicting ship fuel usage, the characteristics analysis of ship energy efficiency data is carried out. The obtained distribution characteristics of ship fuel usage are shown in Fig. 2, and the distribution characteristics of the navigational environments, including wind speeds, wind directions, and wave heights, are shown in Figs. 3–5, respectively. As shown from the analysis results, both meteorological data and ship energy efficiency data have certain sequential characteristics, namely the value of the previous moment's data has an impact on the value of the subsequent moment's data. In addition, those parameters have obvious differences at different times and locations.

To further understand the association between the ship's fuel usage

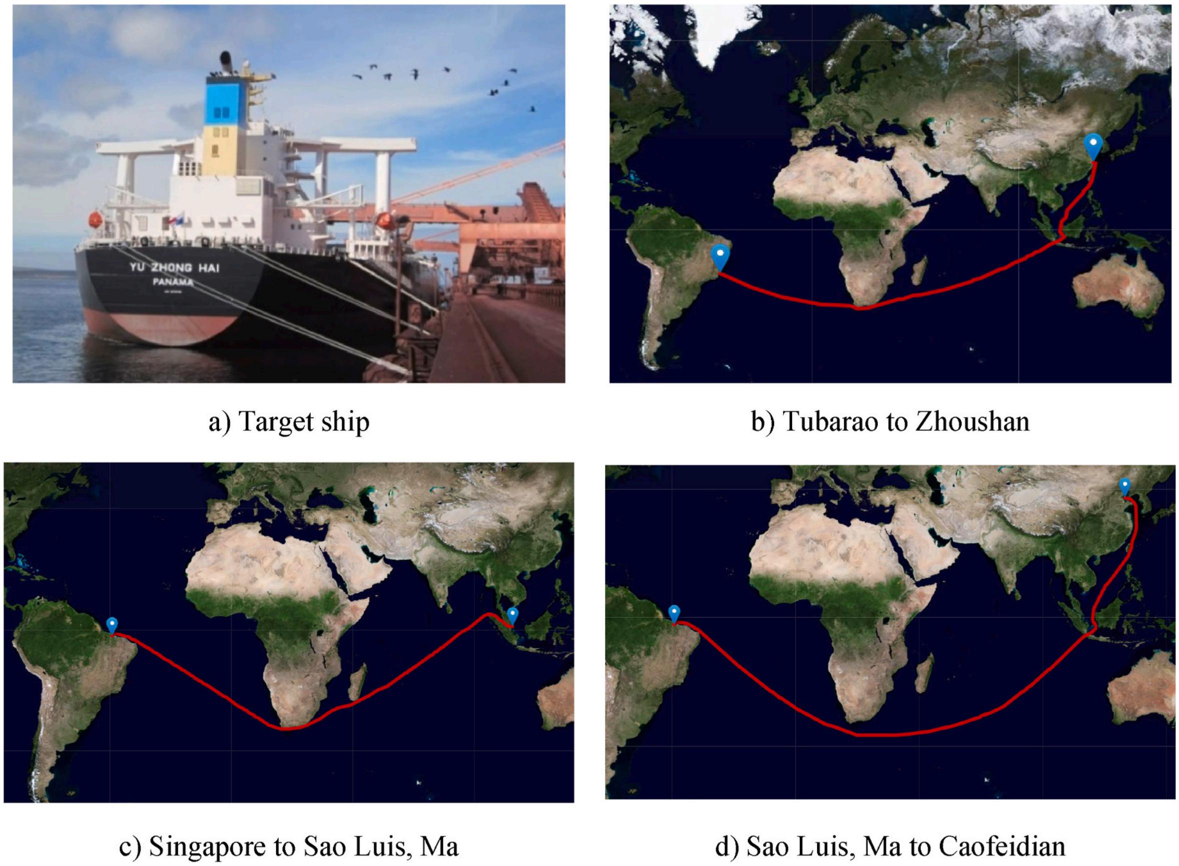


Fig. 13. The diagram of the research objective and the sailing routes.

Table 4
The parameter setting for the GA algorithm [34].

Parameters	Population size	Iteration number	Crossover rate	Mutation rate
Values	10	5	0.5	0.5

Table 5
The parameter setting for the GA-LSTM neural network.

Parameters	Values
Epoch	300
Optimizer	Adma
Loss function	mean_squared_error
Layers	[1,3]
Number of neurons	[32, 256]
Batch_size	[50, 100]
Drop_out rate	0.2

and the multiple influencing parameters, a statistic analysis is conducted [40]. The association relationships are illustrated in Fig. 6, in which the values mean the association degree between the corresponding two parameters.

As it can be seen from the correlation analysis results, the navigational environment factors have a certain effect on the navigation speed, which in turn affects fuel usage of the ship. Hence, the complex navigational environment has a strong correlation with the ship's fuel usage. The statistical analysis of the ship's fuel usage and its multiple influencing parameters is significant for developing the model for ship fuel usage forecast.

3. The GA-LSTM-based model for ship fuel usage forecast

According to the characteristics analysis of the data related fuel usage of the ship, a GA-LSTM-based model for ship fuel usage forecast could be established. The framework of the established GA-LSTM-based model for ship fuel usage forecast is given in Fig. 7, which mainly consist of navigation data acquisition, data processing, model training, and energy consumption prediction. Among others, the model training part based on the GA-LSTM is the key to developing the model for ship fuel usage forecast.

Table 6
Fundamental details of the target ship.

Items	Parameter	Items	Parameter
Length	327 m	Design speed	14.5 kn
Depth	29 m	Number of blades	5
Width	55 m	Diameter of propeller	9.7 m
Deadweight	297,959 t	Engine rated power	19,000 kW
Draft	21.4 m	Engine rated speed	73 rpm

Table 7
Detailed information of different voyages.

Date of the voyage	Departure	Destination	Cargo (t)	Distance (n mile)
2016/07/22–2016/09/09	Tubarao	Zhoushan	292,898	10,988
2016/01/30–2016/03/04	Singapore	SaoLuis, Ma	113,174	9,709
2016/03/04–2016/04/28	Sao Luis, Ma	Caofeidian	288,527	12,570

Table 8
The optimized parameters of the GA-LSTM neural network.

Study case	Parameters	Values
Case 1: Tubarao to Zhoushan	Epoch	300
	Optimizer	Adma
	Loss function	mean_squared_error
	Layers	3
	Number of neurons in the first layer network	199
	Number of neurons in the second layer network	44
	Number of neurons in the third layer network	186
	Batch_size	60
	Drop_out rate	0.2
Case 2: Singapore to Sao Luis, Ma	Epoch	300
	Optimizer	Adma
	Loss function	mean_squared_error
	Layers	3
	Number of neurons in the first layer network	115
	Number of neurons in the second layer network	169
	Number of neurons in the third layer network	262
	Batch_size	60
	Drop_out rate	0.2
Case 3: Sao Luis, Ma to Caofeidian	Epoch	300
	Optimizer	Adma
	Loss function	mean_squared_error
	Layers	3
	Number of neurons in the first layer network	197
	Number of neurons in the second layer network	128
	Number of neurons in the third layer network	166
	Batch_size	50
	Drop_out rate	0.2

3.1. The construction of LSTM neural network

The LSTM was developed primarily to address gradient disappearance and gradient explosion issues for the training of long data sequences [41]. The inputs of the model include ship's operational information and navigational environment factors (such as wave height, wind speed and direction). Compared to other neural networks, the LSTM is more suitable to deal with problems that have sophisticated multi-input variables [42, 43]. The logic structure of the LSTM cell in Fig. 7 is illustrated in Fig. 8 in detail. A single LSTM cell consists of two memory state quantities namely C_t and h_t, three state control gates (namely, the input, forget, and output gate), and the input x_t at moment t, which can make RNN have the ability of long-term memory by adding state control gates.

The forget gate determines how much information of the previous moment memory cell state C_{t-1} is kept in the current moment memory cell state C_t. The input gate determines how much information of the current moment network input x_t is imported to C_t, and the output gate determines the amount of information from C_t that is given to the next moment hidden layer h_t.

The mathematical expression of the forget gate is shown in Eq. (1).

$$f_t = sigmoid\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

where, W_f and b_f represent the forget gate cycle weight and bias, respectively; x_t denotes the input at moment t; $h_{t\text{-}1}$ denotes the memory state quantity at the previous moment t-1.

In addition, the mathematical expression of the input gate is given in Eq. (2).

$$\begin{aligned} i_t &= sigmoid(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \widetilde{C}_t &= \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \end{aligned} \tag{2}$$

where, W_i, W_c, b_i, and b_c represent the input gate cycle weights and biases, respectively.

Moreover, the mathematical expression of the output gate is shown in Eq. (3).

$$\begin{aligned} O_t &= sigmoid(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= O_t \cdot \tanh(C_t) \end{aligned} \tag{3}$$

where, W_o and b_o represent the output gate cycle weight and bias, respectively; C_t denotes the memory state quantity.

The final outputs of the LSTM cell are shown in Eq. (4).

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{4}$$

The LSTM neural network corrects the weight values within the network by forward-passing and back-propagation mechanisms until the network converges.

The established LSTM network consists of the input layer, LSTM layer, Dropout layer, and the fully connected layer. In addition, to avoid the overfitting phenomenon that would weaken the forecast performance and accuracy of the established model, a Dropout layer is imported to the LSTM layer and the fully connected layer. Its working principle of the Dropout layer is illustrated in Fig. 9. The core idea is to make part of the neurons stop working during training and save different neurons in each learning process, so that the model can be less dependent on certain local features and avoid the overfitting phenomenon.

According to the principles of the LSTM neural network, the structures and parameter settings would have a certain influence on the prediction performance of the established energy consumption model. Therefore, it is necessary to optimize the structure and parameters, including the number of neural network lays, the number of neurons per layers, and the number of samples passed to the program for training in a single pass Batch_size, in order to improve the prediction performance of the network.

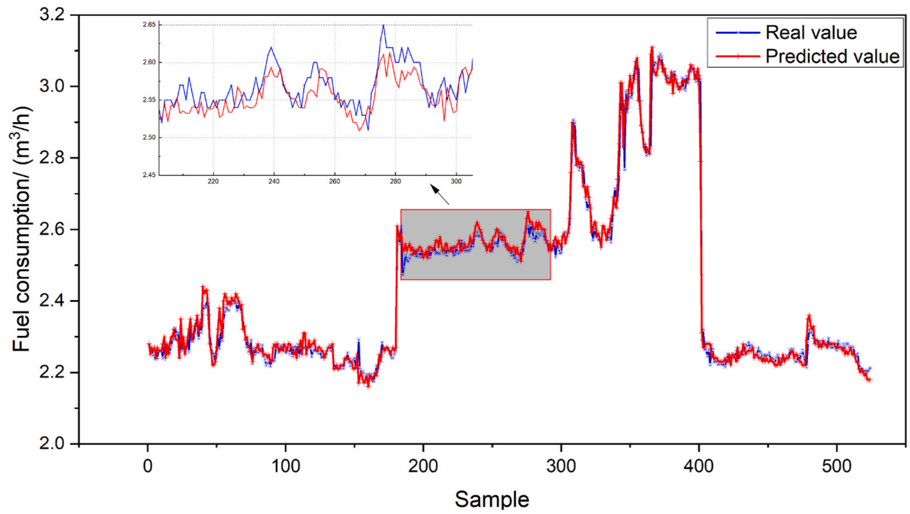
3.2. The implementation processes of the genetic algorithm

GA is a stochastic algorithm that replicates natural selection and the genetic mechanism of biological evolution [44]. The GA represents the solution of the problem as the survival process of chromosomes, and ultimately acquires the optimal solutions of the problem through continuous evolutions of chromosome populations. At the same time, the GA has the advantages of strong merit-seeking ability and easy implementation [18]. Based on those advantages, the GA is adopted to optimize the hyperparameters of the LSTM neural network, which include the number of network layers, the number of network neurons per layer, and Batch_size. The main implementation processes of the GA include encoding, generating the initial population, fitness evaluation, selection, crossover, and mutation, as illustrated in Fig. 10.

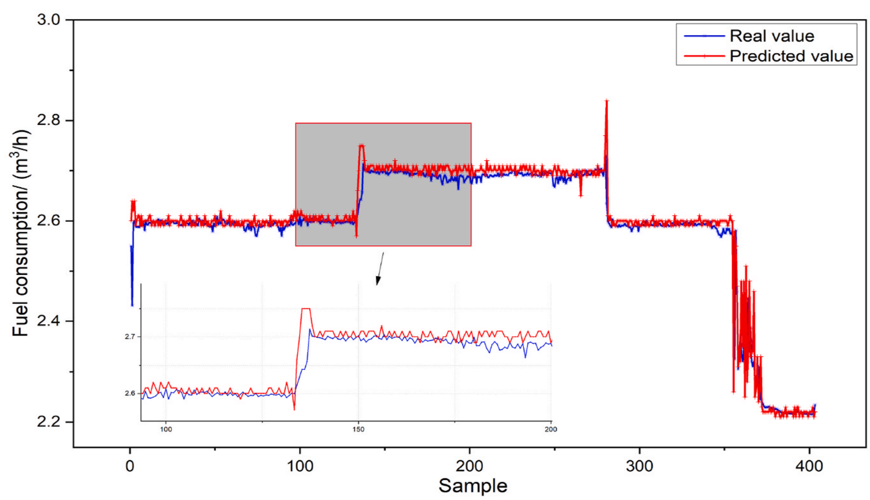
3.3. GA-LSTM-based model establishment for ship fuel usage prediction

The hyperparameters would influence the fitting accuracy of the LSTM network to some extent, and thus it is essential to achieve the best hyperparameters' values, which are suitable for data with different characteristics. However, there is currently no mature theory to obtain suitable values of hyperparameters. Therefore, a comparative analysis method and the GA optimization method are adopted to get the best network hyperparameter values of the LSTM in this paper. The optimizer of the LSTM is chosen by using a comparative analysis method, and the GA is used to tune the parameters in terms of the amount of network layers, neurons, and the Batch_size of the LSTM network.

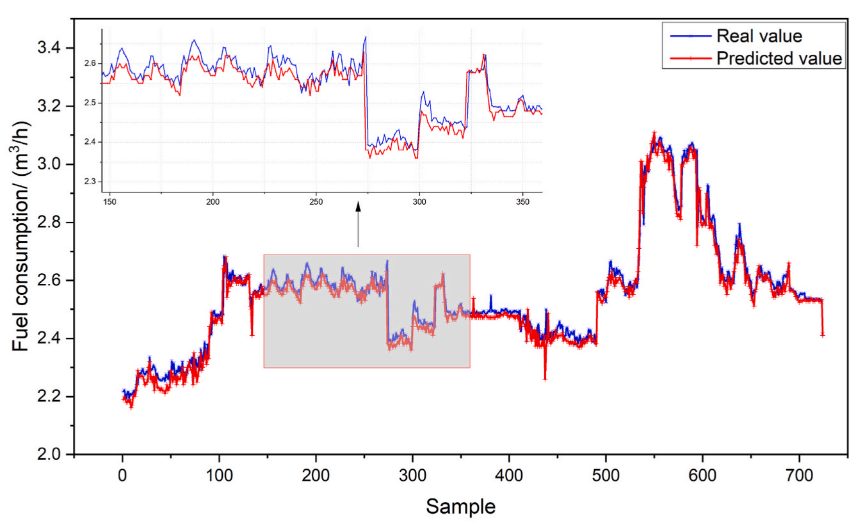
The optimizer is mainly used to adjust the weights and biases in the neural network, thus obtaining the minimal loss function value and improving the model accuracy. In the Tensorflow framework of the Python Environment, the neural network optimizers mainly include Adam, SGD, RMSprop, and Adagrad. However, there are currently no



a) Case 1: Tubarao to Zhoushan



b) Case 2: Singapore to Sao Luis, Ma



c) Case 3: Sao Luis, Ma to Caofeidian

Fig. 14. The obtained prediction results of ship fuel usage.

Table 9
Accuracy analysis of the GA-LSTM-based prediction model.

Study cases	Items	MSE	RMSE	MRE	MAE	R^2
Case 1: Tubarao to Zhoushan	Train dataset	0.0009	0.0296	0.0076	0.0190	0.9860
	Test dataset	0.0012	0.0346	0.0081	0.0201	0.9798
Case 2: Singapore to Sao Luis, Ma	Train dataset	0.0005	0.0214	0.1132	0.0123	0.9576
	Test dataset	0.0007	0.0265	0.0171	0.0126	0.9472
Case 3: Sao Luis, Ma to Caofeidian	Train dataset	0.0007	0.0276	0.1132	0.0192	0.9781
	Test dataset	0.0012	0.0346	0.0096	0.0244	0.9642

The values with 4 decimals after rounding.

specific methods to select the appropriate optimizer, which is generally made through experimental comparison or experience. For the selection of the best optimizer for training LSTM neural networks, the mean absolute error (MAE), and root mean square error (RMSE) are taken as the selection indexes, which can be calculated by Eq. (5) and Eq. (6), respectively.

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|\widetilde{y}_i - y_i| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \widetilde{y}_i)^2} \tag{6}$$

where, $\widetilde{y}_i$ and y_i denotes the predicted and real value, respectively.

The forecast results by using different optimization functions to train the established LSTM network are given in Table 3. The comparison of the errors of different optimization functions is illustrated in Fig. 11. From the comparative analysis results, the Adam algorithm has better prediction accuracy, and thus it is chosen as the optimizer of the established GA-LSTM network.

In addition, the learning and optimization processes of the LSTM network improved through the GA are illustrated in Fig. 12, which specifically include the following steps:

Step 1. Preprocess the data used for training the GA-LSTM network, including the abnormal data cleaning, and data standardization.

Step 2. Initialize the genetic algorithm parameters by setting the size of populations, number of iterations, crossover rate, and variation rate, as shown in Table 4.

Step 3. Iteratively optimize the Batch_size, the amount of layers in the hidden layer, and neural units in the hidden layer by adopting the GA, as shown in Table 5.

Step 4. Determine the network structure and hyperparameter settings of the LSTM according to the GA optimization results. The forecast error in terms of MAE of the GA-LSTM network is taken as the fitness function. Finally, an optimal network is developed by referring to the individual fitness value.

In addition, five error evaluation indexes, including the coefficient of determination (R^2), RMSE, mean relative error (MRE), mean square error (MSE), and MAE, are adopted to evaluate the forecast accuracy of the established GA-LSTM-based model. The R^2, MRE, and MSE are

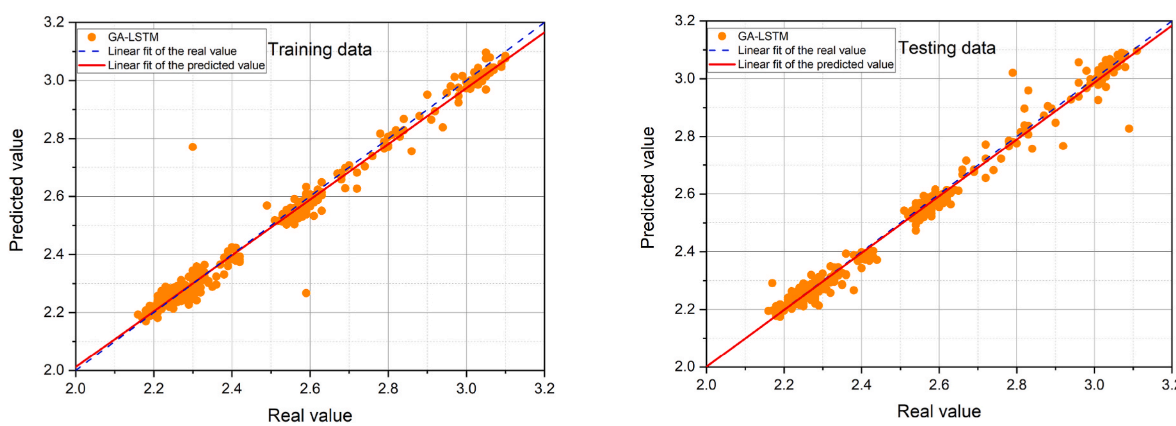


Fig. 15. Case 1: The prediction scatters diagram of the GA-LSTM-based fuel usage prediction model.

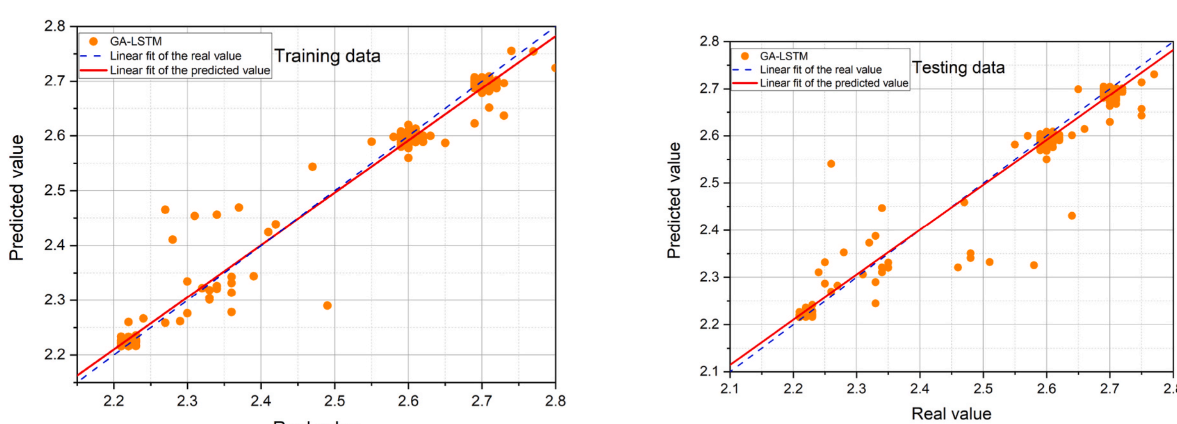


Fig. 16. Case 2: The prediction scatters diagram of the GA-LSTM-based fuel usage prediction model.

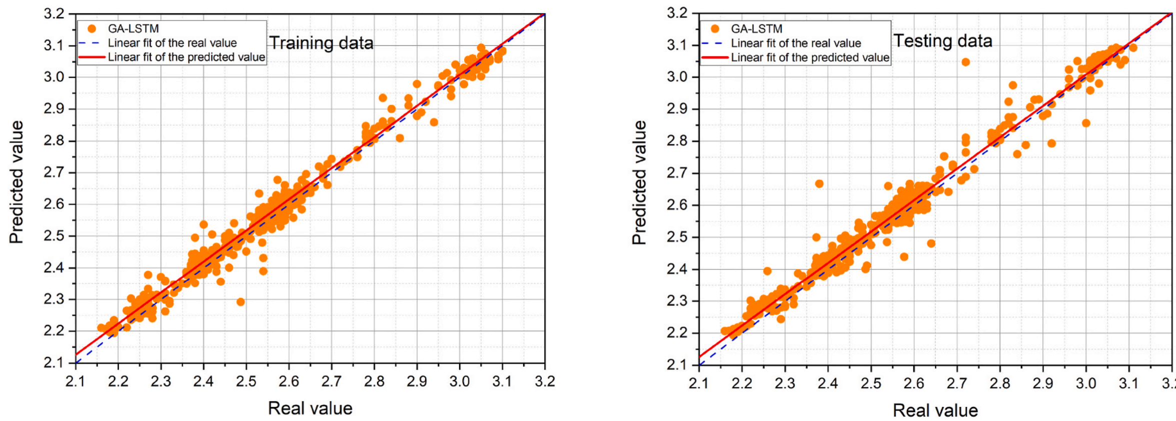


Fig. 17. Case 3: The prediction scatters diagram of the GA-LSTM-based fuel usage prediction model.

shown in Eqs. (7)-(9).

$$R^2 = 1 - \frac{\sum_i (\tilde{y}_i - y_i)^2}{\sum_i (\bar{y}_i - y_i)^2} \tag{7}$$

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (\tilde{y}_i - y_i)^2 \tag{8}$$

$$MRE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\tilde{y}_i - y_i}{y_i} \right| \tag{9}$$

where, $\tilde{y}_i$, y_i and, $\bar{y}_i$ denotes the predicted, real value and average value, respectively.

4. Application analysis of the GA-LSTM-based fuel usage prediction model

4.1. Study case introduction

A Very Large Oil Carrier (VLOC) transporting iron ore between China and Brazil is taken as the research objective. The ship's primary trajectory traverses the South China Sea, the Indian Ocean, and the Atlantic Ocean. The research objectives in terms of the ship and the sailing routes are shown in Fig. 13.

A total of three voyages were taken as the study cases to validate the effectiveness of the established prediction model. Case 1 is the voyage from Tubarao to Zhoushan with a cargo capacity of 292,898 tons and with the sailing distance of 10,988 n miles. Case 2 is the voyage from Singapore to Sao Luis, Ma, with a cargo capacity of 113,174 tons and a voyage distance of 9709 n miles. Case 3 is the voyage from Sao Luis, Ma to Caofeidian with a cargo of 288,527 tons and a voyage distance of 12,570 n miles. In addition, the detailed information of the target ship and the different voyages are given in Table 6 and Table 7, respectively.

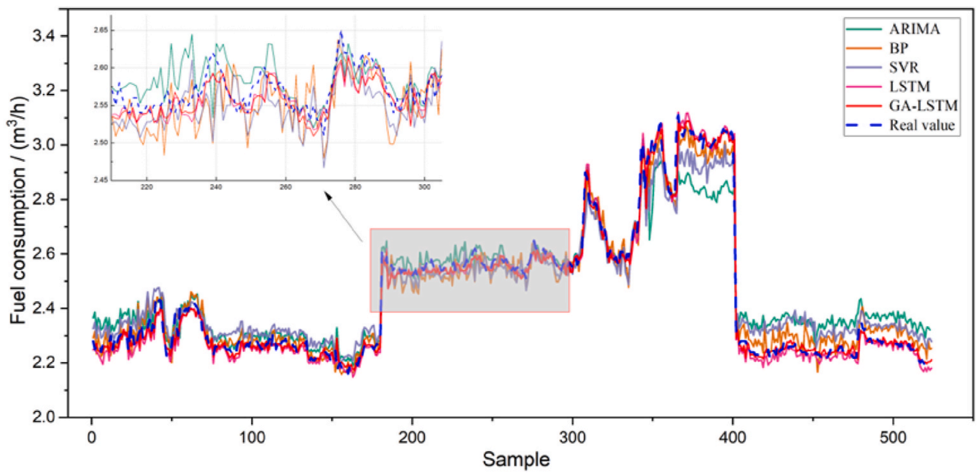
4.2. Analysis of prediction results on the ship fuel usage

Case studies are conducted to demonstrate the established GA-LSTM-based ship energy consumption model. The types of data used to train the model include: trim, heel, wind speed, wind direction, sailing speed, sailing direction, wave height and hourly fuel consumption. Where hourly fuel consumption is used as the model output and other data are used as the inputs of the established model. To eliminate the effect of data dimension and enhance computational performance, the data is normalized to enable the model to obtain valid prediction results. In addition, the data set is split in an interleaved manner when splitting the data set. After data preprocessing, the Case 1 has a total of 1,048 pieces of navigation data, Case 2 has a total of 863 pieces of navigation data, and Case 3 has a total of 1,450 pieces of navigation data. Based on the information of the research objectives, the prediction analysis of ship fuel usage is carried out by using the established GA-LSTM-based prediction model. The obtained parameters of the LSTM model optimized by the GA algorithm are shown in Table 8. The obtained prediction results of ship fuel usage based on the GA-LSTM are given in Fig. 14, and the forecast errors of the established GA-LSTM-based model are shown in Table 9. Additionally, the prediction scatters diagrams of the GA-LSTM-based fuel usage prediction model for different cases are given in Figs. 15-17.

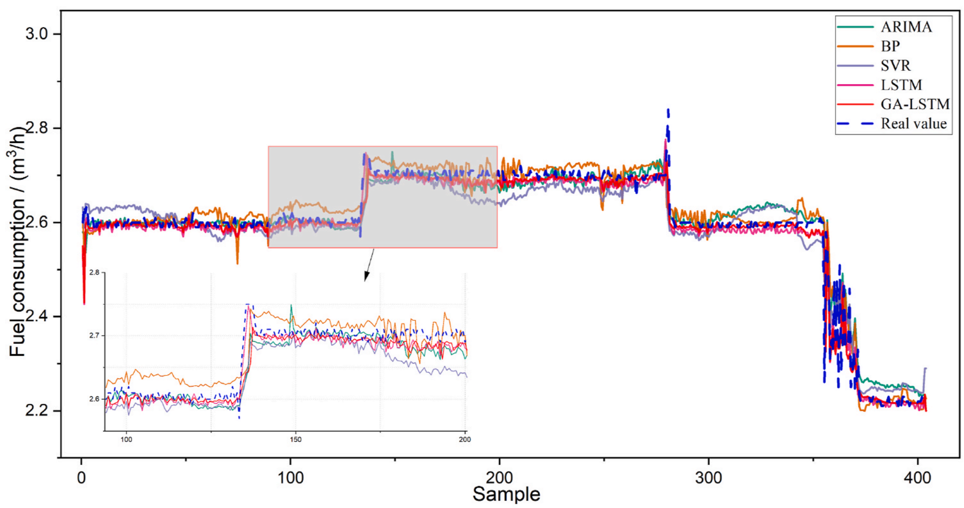
4.3. Comparison of different energy consumption prediction methods

To further demonstrate the forecast performance of the GA-LSTM-based energy consumption model, a comparison analysis of the prediction models adopting various algorithms including the LSTM, BP, SVR, ARIMA, which have been widely adopted for the fuel consumption prediction and time-series parameters forecasting [21, 23, 45], and the established GA-LSTM network based on the same energy consumption data set are carried out (see Fig. 17). The evaluation index value of each model prediction result is used to compare the accuracy of those models. The prediction results of various fuel usage prediction models are given in Fig. 18, and the scatterplots of the prediction results of each algorithm are shown in Figs. 19–21, respectively.

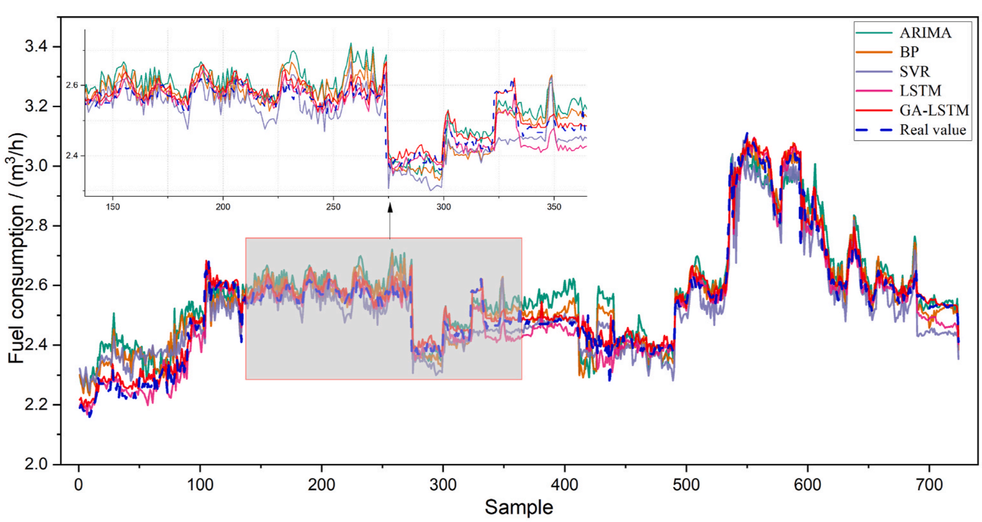
In addition, the comparative analysis of the prediction results of various energy consumption models and the time required to predict the entire test dataset are shown in Table 10, and the prediction errors are shown in Fig. 22. In Case 1, the GA-LSTM-based ship energy consumption prediction model has the highest R^2 value and the lowest MSE, RMSE, MRE, and MAE values. In Case 2, the prediction effect of each prediction model is similar, but the GA-LSTM has smaller prediction error and more accurate prediction compared to other models. The same to Case 1, the prediction accuracy of the GA-LSTM-based ship energy consumption prediction model is higher than that of the traditional LSTM-based model. In Case 3, the prediction accuracy of the GA-LSTM energy consumption prediction model and LSTM energy consumption prediction model is significantly higher than the other comparative models, and the GA-LSTM energy consumption prediction model has a higher prediction accuracy compared to the LSTM energy consumption prediction model. In the three cases, the prediction accuracy of the GA-LSTM energy consumption prediction model is 15.6%, 12.5%, and 14.3% higher than that of the LSTM energy consumption model in terms of MSE, respectively. Therefore, it is not difficult to conclude that the GA optimization can effectively improve the prediction performance of the LSTM-based model. In addition, compared with those prediction models based on ARIMA, BP and SVR, the constructed GA-LSTM-based ship energy consumption model performs better in terms of prediction accuracy. Furthermore, the time consumed for the fuel consumption



a) Case 1: Tubarao to Zhoushan



b) Case 2: Singapore to Sao Luis, Ma



c) Case 3: Sao Luis, Ma to Caofeidian

Fig. 18. The prediction results of various fuel usage prediction algorithms.

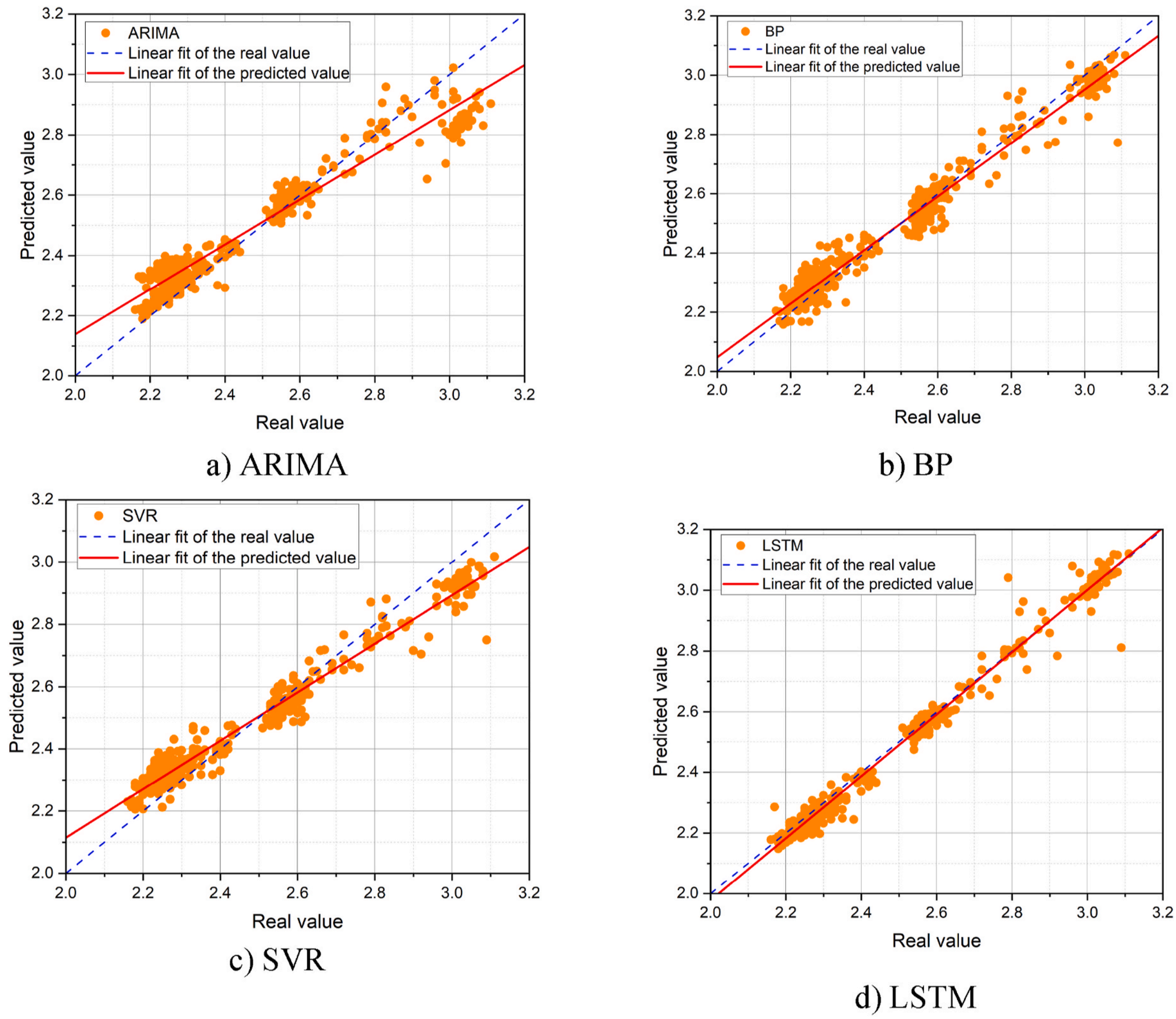


Fig. 19. Case 1: The scatterplots of the prediction results of various algorithms.

prediction of all the different models is within 5 s. That is to say, the established model can achieve rapid prediction of fuel consumption during operation, which can lay a solid foundation for the optimization of ship energy efficiency and thus to reduce fuel consumption and CO_2 emissions.

4.4. The prediction analysis of ship energy efficiency based on the GA-LSTM model

To further validate the practical application effect of the established GA-LSTM-based model for ship fuel usage prediction, the prediction analysis of the ship's operational energy efficiency is conducted. The ship's operational energy efficiency level for a whole voyage can be evaluated through the EEOI, which can be obtained by Eq. (10).

$$EEOI = \frac{\sum_{j} FC_j \times C_{Fj}}{m_{\mathrm{cargo}} \times D} \tag{10}$$

where, j denotes the fuel type, FC_j is the amount of fuel consumption, C_{Fj} denotes the conversion factor of CO_2 emissions for the consumed fuel, m_{cargo} denotes the amount of cargo carried by the ship, and D denotes the distance of the cargo transported.

The fuel used by the target ship is heavy fuel oil (HFO), and the carbon emission information of the fuel is shown in Table 11 [46]. On this basis, the ship's EEOI for the whole voyage can be calculated. The trained GA-LSTM fuel consumption prediction model was also used to validate the prediction of EEOI for the three voyages. The obtained predicted values and measured values are both shown in Table 12.

Through the above case study, it can be seen that the EEOI of the ship derived from the established GA-LSTM-based ship fuel usage model is about 3.42 g/(t n mile) in Case 1, while the EEOI of the ship derived from the actual operation data is 3.43 g/(t n mile), with a prediction error of about 0.29%. In Case 2, the EEOI of the ship using the established GA-LSTM-based fuel usage model is 3.71 g/(t n mile), while the EEOI of the ship based on the actual operational data is 3.74 g/(t n mile), with a prediction error of about 0.81%. In Case 3, the EEOI of the ship using the established GA-LSTM-based ship fuel usage model is 3.17 g/(t n mile), while the EEOI of the ship based on the actual operational data is 3.15 g/(t n mile), with a prediction error of about 0.63%. Therefore, the constructed GA-LSTM-based ship energy consumption model can also realize the prediction of ship operational energy efficiency effectively. The prediction of ship energy efficiency based on the GA-LSTM model can achieve the evaluation of the ship energy efficiency. On this basis, one could know whether the ship could meet the requirement of carbon intensity proposed by the IMO or not, which can contribute to the optimization management of the ship energy efficiency.

5. Conclusions and future research work

The LSTM network, which is more suitable to analyze the data with time-series characteristics, is adopted to establish the prediction model for ship fuel usage. With that, the GA is proposed to tune the network

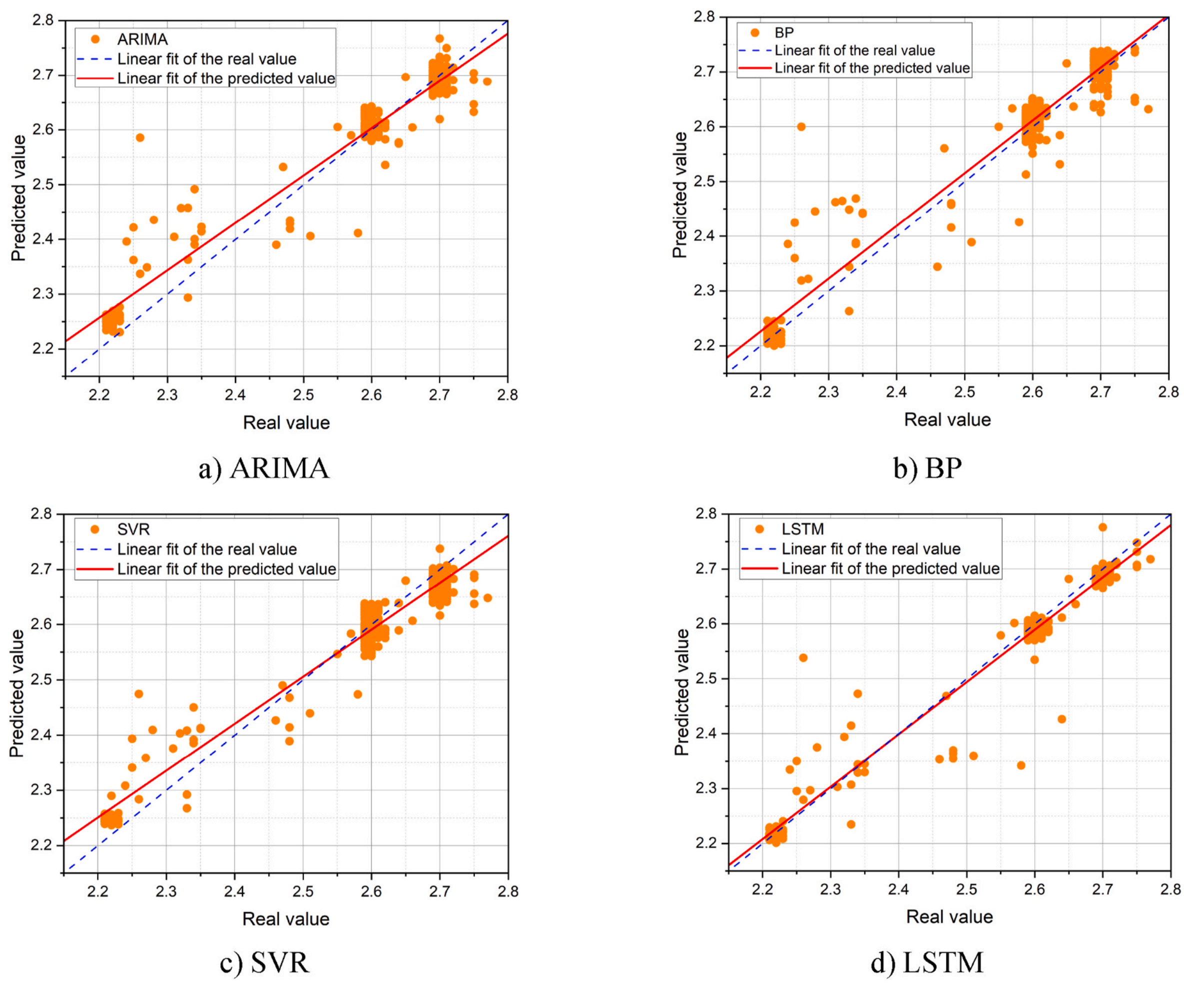


Fig. 20. Case 2: The scatterplots of the prediction results of various algorithms.

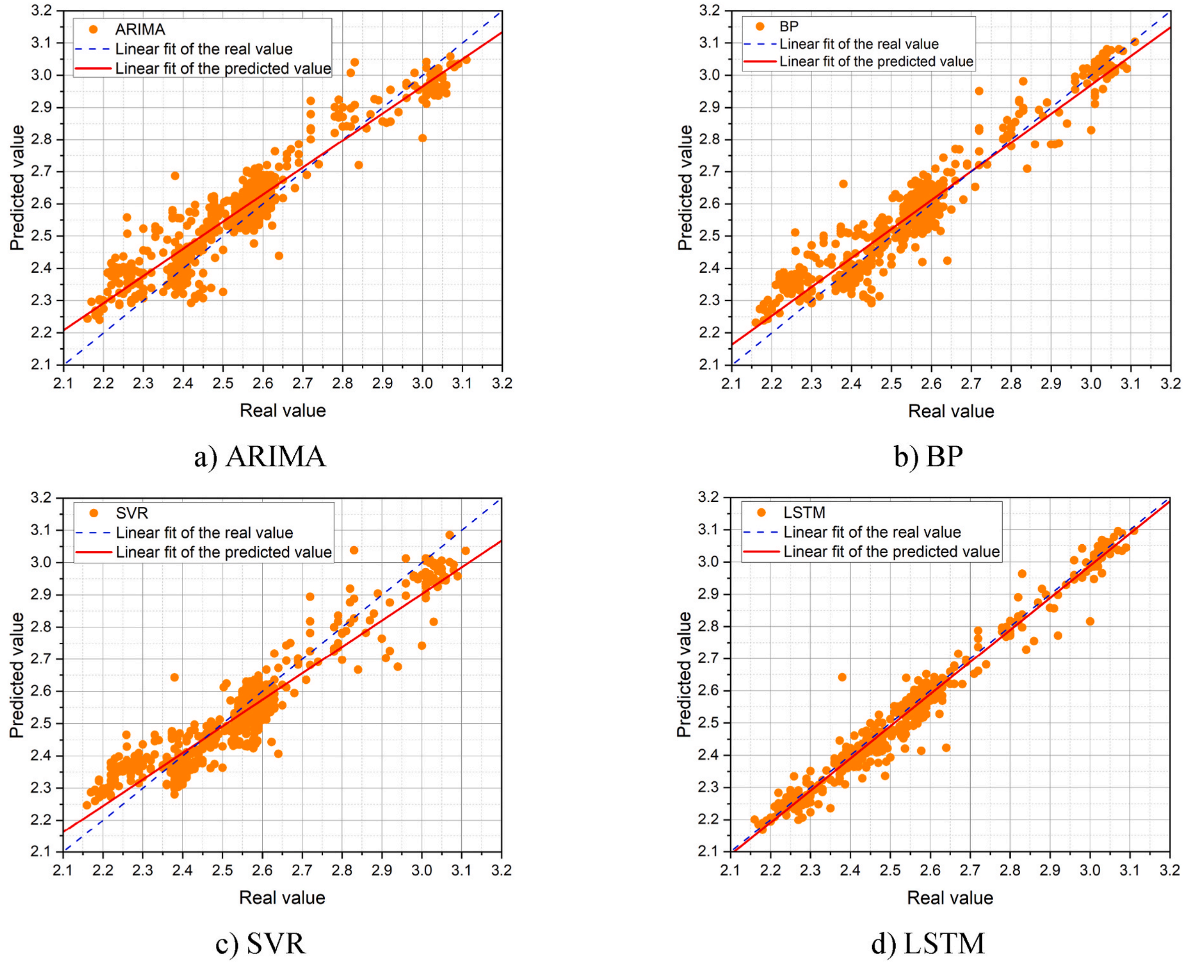


Fig. 21. Case 3: The scatterplots of the prediction results of various algorithms.

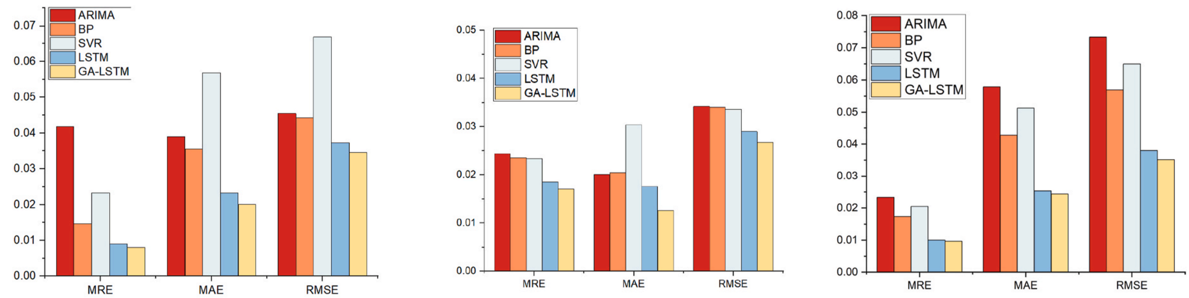
Table 10
Comparative analysis of the forecast results of various approaches.

Study cases	Approaches	MSE	RMSE	MRE	MAE	R^2	Consumed time (s)
Case 1: Tubarao to Zhoushan	ARIMA	0.0021	0.0455	0.0418	0.0391	0.8723	2.2559
	BP	0.0020	0.0443	0.0147	0.0356	0.9596	2.6216
	SVR	0.0045	0.0668	0.0234	0.0569	0.9301	2.6639
	LSTM	0.0014	0.0374	0.0091	0.0233	0.9629	1.7608
	GA-LSTM	0.0012	0.0346	0.0081	0.0201	0.9798	3.4346
Case 2: Singapore to Sao Luis, Ma	ARIMA	0.0012	0.0346	0.0244	0.0201	0.9094	2.4777
	BP	0.0010	0.0316	0.0236	0.0204	0.9396	2.7623
	SVR	0.0014	0.0376	0.0234	0.0304	0.8931	2.6625
	LSTM	0.0008	0.0283	0.0186	0.0176	0.9281	1.9691
	GA-LSTM	0.0007	0.0265	0.0171	0.0126	0.9472	3.1500
Case 3: Sao Luis, Ma to Caofeidian	ARIMA	0.0053	0.0733	0.0233	0.0578	0.8479	2.7070
	BP	0.0032	0.0569	0.0173	0.0427	0.9083	3.8021
	SVR	0.0042	0.0649	0.0205	0.0513	0.8807	2.9070
	LSTM	0.0014	0.0379	0.0125	0.0253	0.9499	3.3662
	GA-LSTM	0.0012	0.0346	0.0096	0.0244	0.9642	4.1408

The values with 4 decimals after rounding.

structures and hyperparameters of the LSTM-based prediction model, thus enhancing the forecast performance of the established energy consumption model. Finally, a GA-LSTM-based model for ship fuel usage forecast is developed, followed by a validation analysis based on the actual operational data. The analysis results show that the forecast accuracy of the established GA-LSTM-based ship energy consumption model is higher than those models adopting BP neural network, support vector machine (SVR), and ARIMA algorithms. Compared with the LSTM network, the forecast accuracy of the established GA-LSTM-based model of ship fuel usage can be effectively improved by adopting the GA optimization, with 15.6%, 12.5% and 14.3% reduction in terms of MSE, respectively. Additionally, the constructed GA-LSTM-based ship energy consumption model can also realize the prediction of ship operational energy efficiency with an error of 0.29%, 0.81% and 0.63%, respectively.

In summary, the LSTM neural network with the structure and hyperparameters optimized by GA can effectively enhance its prediction ability, and thus can achieve more accurate prediction results of ship



a) Case 1: error comparison analysis   b) Case 2: error comparison analysis   c) Case 3: error comparison analysis

Fig. 22. Comparison analysis of the forecast errors of different algorithms.

Table 11
The carbon emission information of different types of fuel.

Fuel types	Reference standard	Carbon content	C_{Fj}
Diesel/Gasoline	ISO8217 DMC-DMX	0.875	3.206
Light Fuel Oil (LFO)	ISO8217 RMA-RMD	0.86	3.151
Heavy Fuel Oil (HFO)	ISO8217 RME-RMK	0.85	3.114
Liquefied Petroleum Gas (LPG)	Propane	0.819	3.000
	Butane	0.827	3.030
Liquefied Natural Gas (LNG)	/	0.75	2.750
Methanol	/	0.375	1.375
Ethanol	/	0.5217	1.913

Table 12
Comparison of the EEOI prediction results.

Study cases	Items	Distance (n mile)	Cargo (t)	Fuel consumption (t)	EEOI [g/(t n mile)]
Case 1: Tubarao to Zhoushan	Predicted value	10,988	292,898	3536.65	3.42
	Measured value	10,988	292,898	3542.57	3.43
Case 2: Singapore to Sao Luis, Ma	Predicted value	253,174	113,174	2928.52	3.71
	Measured value	253,174	113,174	2952.21	3.74
Case 3: Sao Luis, Ma to Caofeidian	Predicted value	12,570	288,527	3691.93	3.17
	Measured value	12,570	288,527	3671.22	3.15

fuel usage and ship's operational energy efficiency level. It is worth mentioning that, the established model could still achieve the effective prediction of the ship energy consumption after training and learning if the obtained data could reflect the conditions of the hull and propeller as the internal part of the overall ship. It is important to promote the progress of ship energy efficiency optimization technology. In the future, more intelligent technologies would be studied to continuously improve the forecast performance in terms of accuracy and applicability of the ship energy consumption model in different operational scenarios. Moreover, with the prediction model, an optimization method and system for the management of ship fuel usage would be developed, which will be of great significance for reducing the fuel usage and carbon emissions, and thus contributing to the decarbonization of the shipping industry.

Author statement

Kai WANG: Conceptualization, Methodology, Investigation, Software, Validation, Funding acquisition, and Writing - Review & Editing. **Yu HUA:** Conceptualization, Investigation, Software, Writing-Original draft preparation, Validation, Visualization. **Lianzhong HUANG:** Conceptualization, Methodology, Supervision and Project administration. **Xin GUO:** Investigation, Writing-Original draft preparation, Validation and Visualization. **Xing LIU:** Methodology, Software, Visualization, and Writing - Review & Editing. **Zhongmin MA:** Methodology, Writing - Review & Editing. **Ranqi MA:** Investigation, Software, Writing - Review & Editing. **Xiaoli JIANG:** Methodology, Investigation, and Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgements

The authors are grateful to the support of the National Natural Science Foundation of China (52271305, 52071045), the National Key R&D Program of China (2022YFB4300803), and Fundamental Research Funds for Universities (LJKQZ2021009, LJKMZ20220360), the Fundamental Research Funds for the Central Universities (3132023211, 3132023525).

References

[1] Pallotta G, Vespe M, Bryan K. Vessel pattern knowledge discovery from AIS data: a framework for anomaly detection and route prediction. Entropy 2013;15:2218–45.
[2] Li B. The status quo of energy saving and emission reduction in shipping industry and its approach to low-carbon development. J Eng Stud 2012;4(3):260–9.
[3] Li HJ, Jia P, Wang XJ, et al. Ship carbon dioxide emission estimation in coastal domestic emission control areas using high spatial-temporal resolution data: a China case. Ocean Coast Manag 2023;232:106419.
[4] Fourth IMO. IMO GHG Study 2020-Final report. IMO; 2020.
[5] IMO. Guidelines on operational carbon intensity indicators and the calculation methods (CII GUIDELINES, G1). Resolution MEPC 2021;336(76):6–17. 2021.
[6] IMO. IMO Train the Trainer (TTT) course on energy efficient ship operation-M2 Ship energy efficiency regulations and related guidelines. IMO; 2016.
[7] Nicoleta A, Ovidiu CA. Improving the voyage energy efficiency by using EEOI. Procedia - Soc Behav Sci 2014;138:531–6.
[8] Hu Z, Zhou T, Osman MT, et al. A novel hybrid fuel consumption prediction model for ocean-going container ships based on sensor data. J Mar Sci Eng 2021;9(449):1–19.

[9] Uyank T, Karatuğ Ç, Arslanolu Y. Machine learning approach to ship fuel consumption: a case of container vessel. Transport Res Transport Environ 2020;84: 102389.
[10] Wang K, Wang JH, Huang LZ, Yuan YP, Wu GT, Xing H, Wang ZY, Wang Z, Jiang XL. A comprehensive review on the prediction of ship energy consumption and pollution gas emissions. Ocean Eng 2022;266:112826.
[11] Su ZQ, Wu CL, Xiao YJ, He HD. Study on the prediction model of accidents and incidents of cruise ship operation based on machine learning. Ocean Eng 2022;260: 111954.
[12] Wang K, Guo X, Zhao JH, Ma RQ, Huang LZ, Tian F, Dong SY, Zhang P, Liu CL, Wang Z. An integrated collaborative decision-making method for optimizing energy consumption of sail-assisted ships towards low-carbon shipping. Ocean Eng 2022;266:112810.
[13] Wang K, Xue Y, Xu H, Huang LZ, Ma RQ, Zhang P, Jiang XL, Yuan YP, Negenborn RR, Sun PT. Joint energy consumption optimization method for wing-diesel engine-powered hybrid ships towards a more energy-efficient shipping. Energy 2022;245:123155.
[14] Pagoropoulos A, Moller AH, McAloone TC, et al. Applying Multi-Class Support Vector Machines for performance assessment of shipping operations: the case of tanker vessels. Ocean Eng 2017;140:1–6.
[15] Gkerekos G, Lazakis I, Theotokatos G. Machine learning models for predicting ship main engine fuel oil consumption: a comparative study. Ocean Eng 2019;188: 106282.
[16] Wang SZ, Ji BX, Zhao JS, et al. Predicting ship fuel consumption based on LASSO regression. Transport Res Part D 2018;65:817–24.
[17] Hu ZH, Jin YX, Zhou TR, Hu QY. Real-time prediction of ship energy consumption based on XGBoost. J Shanghai Marit Univ 2022;43(1):23–29+37 (in Chinese).
[18] Yang LQ, Chen G, Rytter NGM, et al. A genetic algorithm-based grey-box model for ship fuel consumption prediction towards sustainable shipping. Ann Oper Res 2019:1–27.
[19] Jeon M, Noh Y, Shin Y, et al. Prediction of ship fuel consumption by using an artificial neural network. J Mech Sci Technol 2018;32(12):5785–96.
[20] Liang Q, Tvete HA, Brinks HW. Prediction of vessel propulsion power using machine learning on AIS data, ship performance measurements and weather data. J Phys Conf 2019:1357.
[21] Bal Beşikçi EB, Arslan O, Turan O, et al. An artificial neural network based decision support system for energy efficient ship operations. Comput Oper Res 2016;6: 393–401.
[22] Hu ZH, Jin YX, Hu QY, Sen S, Zhou TR, Mohd TO. Prediction of fuel consumption for enroute ship based on machine learning. IEEE Access; 2019.
[23] Yan XP, Sun X, Yin QZ. Multiparameter sensitivity analysis of operational energy efficiency for inland river ships based on backpropagation neural network method. Mar Technol Soc J 2015;49:148–53.
[24] Shen XQ, Wang SZ, Xu T, et al. Ship fuel consumption prediction under various weather condition based on DBN. 21-23. In: Proceedings of 12th international conference on marine navigation and safety of sea transportation; June 2017. Gdynia, Poland.
[25] Zhao CJ. Collection and application of ship energy consumption data based on image recognition technology. Microprocess Microsyst 2021;80:103568.
[26] Wang K, Yan XP, Yuan YP, et al. Real-time optimization of ship energy efficiency based on the prediction technology of working condition. Transport Res Transport Environ 2016;46:81–93.
[27] Lee JB, Roh MI, Kim KS. Prediction of ship power based on variation in deep feed-forward neural network. Int J Nav Archit Ocean Eng 2021;13:641–9.
[28] Alonso JM, Alvarruiz F, Desantes JM, et al. Combining neural networks and genetic algorithms to predict and reduce diesel engine emissions. IEEE Trans Evol Comput 2007;11(1):46–55.
[29] Jorges C, Berkenbrink C, Stumpe B. Prediction and reconstruction of ocean wave heights based on bathymetric data using LSTM neural networks. Ocean Eng 2021; 232:109046.
[30] Wang JQ, Du Y, Wang J. LSTM based long-term energy consumption prediction with periodicity. Energy 2020;197:117197.
[31] Gao DW, Zhu YS, Zhang JF, et al. A novel MP-LSTM method for ship trajectory prediction based on AIS data. Ocean Eng 2021;228:108956.
[32] Yuan Z, Liu JX, Zhang Q, Liu Y, Yuan Y, Li ZZ. Prediction and optimization of fuel consumption for inland ships considering real-time status and environmental factors. Ocean Eng 2021;221:108530.
[33] Zhu Y, Zuo Y, Li T. Predicting ship fuel consumption based on LSTM neural network. 7th international conference on information, cybernetics, and computational social systems (ICCSS). IEEE; 2020. p. 310–3.
[34] Shahid F, Zameer A, Muneeb M. A novel genetic LSTM model for wind power forecast. Energy 2021;223:120069.
[35] Peng L, Liu S, Liu R, Wang L. Effective long short-term memory with differential evolution algorithm for electricity price prediction. Energy 2018;162:1301–14.
[36] Duan JD, Wang P, Ma WT, et al. Short-term wind power forecasting using the hybrid model of improved variational mode decomposition and Correntropy Long Short -term memory neural network. Energy 2021;214:118980.
[37] Zhou JJ, Li ZF. Improved genetic algorithm to optimize BP neural network. In: IEEE 10th joint international information technology and artificial intelligence conference (ITAIC); 2022. p. 1347–50.
[38] Nikbakht S, Anitescu C, Rabczuk T. Optimizing the neural network hyperparameters utilizing genetic algorithm. J Zhejiang Univ - Sci 2021;22(6): 407–26.
[39] Wang K, Xu H, Huang LZ, et al. Analysis of intelligent prediction method of ship energy consumption based on machine learning. Ship Eng 2020;42(11):87–93 (in Chinese).
[40] Hu ZH, Zhou TR, Zhen R, et al. A two-step strategy for fuel consumption prediction and optimization of ocean-going ships. Ocean Eng 2022;249:110904.
[41] Sepp H, Jürgen S. Long short-term memory. Neural Comput 1997;9(8):1735–80.
[42] Yuan Z, Liu JX, Zhang Q, Liu Y, Li ZZ. Prediction and optimisation of fuel consumption for inland ships considering real-time status and environmental factors. Ocean Eng 2020;221:108530.
[43] Kim J, Jung C, Kang D, Lee CJ. A new vessel path prediction method using Long Short-term Memory. Trans Kor Inst Electr Eng 2020;69(7):1131–4.
[44] Subramanian R, Jyothish PV, Anantha SV. Genetic algorithm based design optimization of a passive anti-roll tank in a sea going vessel. Ocean Eng 2020;203: 107216.
[45] Ning YR, Kazemi H, Tahmasebi P. A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet. Comput Geosci 2022;164:105126.
[46] IMO. Guidelines for voluntary use of the ship energy efficiency operational indicator (EEOI), MEPC.1/Circ.684. August 2009.
[47] Chi HT, Pedrielli G, Ng SH, et al. A framework for real-time monitoring of energy efficiency of marine vessels [J]. Energy 2018;145:246–60.
[48] International Maritime Organization (IMO). Prevention of air pollution from ships: assessment of IMO efficiency measures for the control of GHG emissions from ships. London: IMO; 2010.
[49] Chang C, Wang C. Evaluating the effects of speed reduce for shipping costs and CO_2 emission. Transport Res Transport Environ 2014;31:110–5.