ANALYSIS AND PREDICTION OF FUEL CONSUMPTION OF MAIN ENGINE USED IN OCEAN SHIP BASED ON VOYAGE DATA

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Abstract

The major expense of sailing for ocean ships is the fuel consumption of the main engine. This study aims to directly reflect the multiple influencing factors of the fuel consumption of the ship's main engine (SME) during navigation and accurately predict the change in fuel consumption of the SME in the future, allowing the shipping company to take reasonable energy-saving and emissions-reduction measures. The ship cruise was the subject of this paper's data mining and analysis. Furthermore, the BP neural network model was used to provide a visual representation of both the SME's fuel use and its related influencing elements, as well as to forecast the boats' fuel consumption throughout a sailing time. Furthermore, the predicted outcomes of the BP neural network model and the standard model in terms of fuel consumption prediction were compared. The impact of the main engine's consumption characteristics, the difference value of draft, and the shipping speed on the ship's fuel consumption during navigation was clearly portrayed on the SME's visual display. The fuel consumption of the ship's main engine, as predicted by the BP neural network model based on trip data, was determined to be more accurate than the figure anticipated by the conventional model. Furthermore, the BP neural network model based on voyage data can not only estimate the ship's various navigation conditions but also accurately predict the changing trend of fuel consumption, and it can be used as one of the factors to consider when a shipping company manages ocean ship navigation.

Key Words

Big data; main engine fuel consumption; fuel consumption prediction; BP neural network

1. Introduction

The shipping industry occupies a major proportion in the transportation industry, about 90% of the trade is completed by the international shipping industry [1]. However, the high fuel consumption of the ship can result in high shipping costs and additional waste emissions, which increases not only the economic cost of the shipping industry but also the emission of harmful gases. Studies have shown that the fuel consumed by the main engine of the ship accounts for 70%–90% of the total fuel [2]. Furthermore, in 2020, the global ship fuel cost just rose to $60 billion to meet the fuel sulfur ceiling of 0.5% stipulated by the international maritime organisation. In addition, from EEDI for new shipbuilding and SEEMP for all ships through the required method for collecting and reporting ship fuel consumption data, to regulations like EEXI, CII, and GCII that are rating for existing ships, the IMO has taken continual activities to develop a succession of environmental evaluation and restriction measures. However, without further theories or techniques that may aid regulatory authorities in better controlling the fuel consumption range of each ship, the relevant departments and corporations would have few clues to address the improvement of planning operations. Therefore, to decline both of the transport cost and the emissions, it is significant to decrease the fuel consumption by replanning the strategies about energy usage and navigation routine.

Moreover, stepping into the era of information, data mining has become one of the most important approaches to improve resource management and energy consumption forecasting. On top of this, to meet the needs of this rising trending, a series of regulations that the 69th meeting of the Marine Environment Protection Committee (MEPC) organised by the IMO stated just provide a steady basement for the collection and mining of voyage data [3]. In terms of this, though more and more researches based on traditional theories has occurred with considerable traceability and interpretability, there is still room for improvement in the accuracy and efficiency of the forecasting as well as analysis. Also, using ordinary analysis methods to predict dynamic consumption needs more data and sensors, which leads to additional costs. So, in order to provide the theoretical basis for the rational replanning of operation as well as maintenance to promote environmental protection and energy efficiency, an approach based on BP neural network of ship main engine fuel consumption is constructed for the prediction, analysis and visualisation

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Recommended by Huaicheng Yan
(DOI: 10.2316/J.2024.206-0635)

of ship main engine fuel consumption, which is also proved to have enough efficiency and accuracy comparing with the traditional fuel consumption prediction models based on ship motion.

2. Literature Review

Many researchers' study priorities in the current international context include the effective reduction of transportation costs and pollution emissions through ship fuel consumption management. Improved energy efficiency of ships will contribute to environmental sustainability, as well as the prosperity and expansion of marine supply chains and transportation [4], [5]. Generally, the proportion of fuel consumed can approximately account for 75%, 17%, and 8% of the main engine (SME), auxiliary engine and fuel boiler, respectively. Therefore, the performance and change of the fuel consumption of the SME is an important basis and indicator for the fuel consumption management, which causes the fuel consumption prediction of the SME also become a hot research field.

From the prospective of methods, the limitation of the traditional methods, which only conclude the indicators of the vehicles themselves like ships' engine and other structures, hinders the use of complex factors about voyage environment as well as creatures. Of course, those methods work well under few or relatively controllable environmental factors, but when the navigation conditions are poor or the impact of environmental factors cannot be ignored, they will inevitably lead to calculate inaccuracy. For example, Yuan *et al.* [6] analysed and predicted the fuel consumption of the inland ship in detail with the DBPNN method and various variables (speed over ground, course over ground, engine speed, engine temperature, water level, water speed, wind speed, wind angle, and segment ID), finding that the performance of the prediction model can be significantly improved after adding environmental data and segment ID as input feature variables. Also, Kim *et al.* [7] found that the model cases using ANN (rather than the regression one) after selecting variables (revolutions per minute of main engine, speed over the ground, speed through water, relative wind speed, relative wind direction, rudder angle, mean draught, trim, displacement, and wetted surface area) with domain-knowledge and LASSO regularisation had a smaller prediction error. Afterwards, with the advancement of relevant theories, a large number of fuel consumption prediction studies incorporating complex environmental elements have gradually emerged in recent years, but theoretical derivation research becomes rare and has significant limits. For example, combined with various current empirical methodologies, Tillig and Ringsberg [8] proposed a four degree of freedom (DOF) balancing simulation model to forecast the fuel consumption of offshore ships Although this approach completely analyses the external forces and moments induced by the environment, it cannot provide precise dynamic data in real time owing to the limits of the algorithm itself (it takes roughly 320 s to complete a 4DOF analysis), hence it is better suited to the hull's early design stage.

From the prospective of the applications and solution, fuel consumption prediction research is more complicated and efficient now, involving multi-constraint analysis based on machine learning and neural networks, as well as various regression models and operation platforms. This is due to the varied nature of the maritime environment, which renders the classic multiple linear regression approach incapable of thoroughly solving associated problems [9] or low efficiency and return [10]. Some researchers have attempted to find and realise simultaneous prediction and optimisation of fuel consumption using a neural network combined with a traditional model [11], [12] or other tools (like the weather routing tool [13]), but more scholars prefer to use machine learning to improve the efficiency of different neural network structures or regression models. With the combination of ANN, many researchers add more environmental or additional factors into their models and lead to better performances. For example, Jeon *et al.* [14] used ship states, engine operations, navigation speed, and weather conditions to predict the fuel consumption and discovered that ANN has higher accuracy and efficiency than polynomial and SVM after optimising the number of hidden layers, neurons, and function types. By comparison, Vujovic *et al.* [15] analysed daily fuel use using a non-uniform time frame (related fuel consumption with years and seasons) and felt and feels that the popular ANN is not always a necessary forecast approach. Hu *et al.* [16] discovered that when comparing the performance of BP and GP, GP requires nearly 150 times the operation time when the accuracy is slightly higher than BP, while its practicability in real-time fuel consumption prediction is far lower than BP. Taking the various demands of businesses into account, Kee and Simon [17] added travelled distance, travelled hours, consumption metric, and wind speed into consideration, instead of seeking for a universal and efficient training model. In the fuel consumption prediction ANN model of Zheng *et al.* [18] considered the arrival time constraints and the uncertainty of ship state (the start and end date for each route, distance sailed, average speed, average load, and fuel consumption in liter per nautical mile) to obtain the change rule through historical data fitting. Tarelko and Rudzki [19] carried out the prediction for the decision-making variables for numerous of uncontrollable variables and disturbances (engine rotational speed, propeller pitch, wind direction angle, wind speed, state of the sea, tidal current direction angle, tidal current speed, time since the last docking of the ship, hourly fuel consumption rate, and instantaneous speed over the ground), finding that the developed ANNs setting up black-box models can be used to build the decision support system aiding selection of the commanded output of ship driveline system. With a procedure based on artificial neural networks, Moreira *et al.* [20] provided estimations of ship speed and fuel oil consumption (from the output torque of the main engine, the revolutions per minute of the propulsion shaft, the significant wave height, the peak period of the waves, and the relative angle of wave encounter measurements), and found that it is possible to predict the consumption with only the sea conditions. Using the LSTM neural network, Yuan *et al.*

[21] analysed and modelled the real-time fuel consumption of inland ships based on the multi-source data composed of monitoring data and hydrological data (designed length, moulded breadth, moulded depth, deadweight, designed draught, designed speed, main engine rated power, main engine rated speed, and propeller diameter).

Based on the research in the above-mentioned literature, it can be found that the prediction of the fuel consumption of the SME is a hot research field. Compared with the ship's traditional models, especially with multiple linear regression and other multi-constraint equations, this paper utilises BP neural network to predict the ship's conditions based on the in-depth learning of the ship's voyage data. To sum up, a large number of scholars have changed their study approaches into machine learning which is more effective to forecast fuel consumption, and most of them tended to consider variables from environment as well as other uncontrollable variables. However, the researches haven't compared all the perspectives as well as various characteristics of those AI methods. And even though some of the studies considered more and more uncertain variables from the environment, their sailing processes were not accidental and the occurrence of bad weather which frequently occurs at sea were not fully considered. So, there still needs more studies that dig out other specific features of other ML models. Though there are some studies' predicted results of the random forest algorithm are significantly better than that predicted by the BP neural network [14], this may be due to the limited amount of voyage data and the lack of diversity of data. By contrast, this paper has realised accurate fuel consumption prediction based on the in-depth study of huge voyage data, which covers all kinds of complex conditions encountered by the ship during navigation.

3. Analysis of Influencing Factors of the Fuel Consumption of Main Engine

3.1 Main Processing Methods for Voyage Data

There are many kinds of data generated by the ship during navigation. These data cover almost all the dynamic changes of the ship on the voyage. Besides, the main characteristics of these data are large, incomplete, noisy, fuzzy, *etc.* The main tasks of voyage-related big data preprocessing include cleaning, classification, transformation, analysis, and modelling of a large amount of centralised data, and then extracting key data that is useful for analysis and prediction. The objective of this paper is to complete the denoising, classified statistic and correlation analysis of voyage-related big data, so as to realise the visual analysis of the big data related to the fuel consumption of the ship during navigation, and further prediction. And in this case, the actual data of the ship is as follows. The total length is 365.90 m, the length between perpendiculars is 348.9 m, the molded breadth is 51.2 m, the maximum height is 67.0 m, the total tonnage is 153,666, the displacement under no load is 45,712, the displacement at full load is 202,322, and the fuel consumption of the main engine is 177.58 g/kwh.

The ship-related data, such as the ship's own data, the sea conditions and the weather, is time-series data, which is collected as an input to the analysis of big data. In this article, data for the condition of main engine (such as fuel consumption, fuel consumption ratio, power, the propeller propulsion efficiency, and so on), the status of ship (like the ship speed, the cargo on board, the width & length of the ship at the waterline and so forth) and environment factors (including the wave speed, the wind speed, the drag coefficient for the wave resistance, and so on) was collected by sensors to make sure the dataset can meet the need of model training. Data denoising can eliminate noise, deviation and outlier in the original data. In respect of data denoising, if the difference between collected adjacent data is large, or if the collected data makes the value of the input or output variable exceed the reasonable range of the variable, such anomalous data will be deleted. Classified statistic is the purposeful classification and statistics of the voyage data of ships, and to select the data which is highly correlated with the ship's navigational status, such as the fuel consumption and power of main engine, the ship speed, the difference value of draft, *etc.* Correlation analysis can be applied to study the regularity and correlation between two or more variables. Also, correlation analysis allows one variable to be inferred from another. For example, if the ship speed is fast, the power of main engine is also high.

3.2 Visual Analysis of the Fuel Consumption of Main Engine Used in an Ocean Ship

The single data used in this paper is the cumulative amount of crude oil consumed by the main engine of an ocean ship every 15 min, and the full data consists of the data from this ocean ship for nearly a year (all the data in the case is from the same dataset). The data obtained when the ship is sailing at sea is selected, and the data when not sailing is deleted, since a lot of data, which is related to staying in the port, anchoring, manoeuvering, *etc.*, is not obtained from the ocean ship that is sailing at sea. The fuel consumption of the SME is shown in Fig. 1. The ordinate axis of Fig. 1 represents the fuel consumption of the SME within 15 min, and the unit is the metric ton. Besides, the horizontal axis denotes the 11 different navigational stages (A∼K) when the ship is sailing at sea. Besides, L at the far right of the box plot covers all navigational stages, *i.e.*, the full navigation, including staying in the port, anchoring, *etc.* The two ends of the box in Fig. 1 are the upper and lower quartiles, respectively, and the horizontal line inside the box is the median, and the small rectangle inside the box is the average. Based on the overall distribution of fuel consumption shown in Fig. 1, in addition to reasons, such as navigation tasks, time, *etc.*, there is a big difference in the fuel consumption among B, G, and H. The main fuel consumption in other navigational stages is between 1 and 1.75 metric tons, and the average fuel consumption of the ship during different navigational stages is closer to 1–1.5 metric tons. In all navigational stages, the distribution range of fuel consumption is large in B, D, E, and K

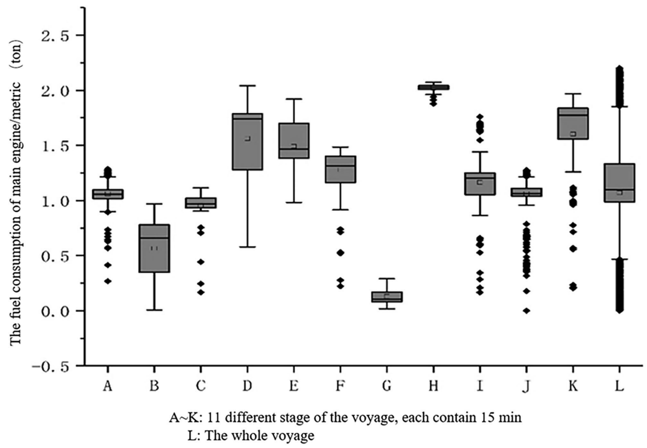

Figure 1. Box plot of the fuel consumption of the main engine used in an ocean ship.

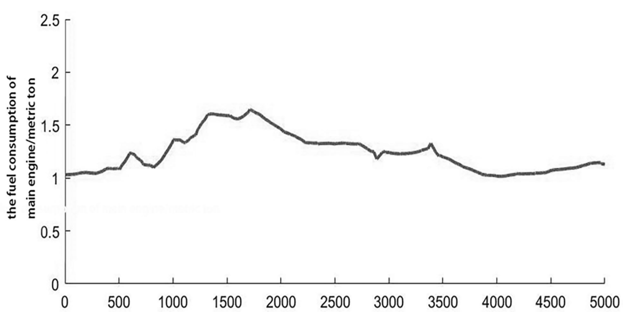

Figure 2. Change in the expected values of the fuel consumption of the SME.

stages, indicating variable sailing conditions of the ship. There are more outliers in some navigational stages shown in Fig. 1, especially in the full navigation (L), because the data obtained at this stage is far more than others. Therefore, the total deviation increases significantly as the proportion is similar. Moreover, since the box plot has strong resistance, the outliers do not affect the shape of the data distribution in the box plot.

As one of the intuitive measures of navigation performance and optimisation effect, the change in the expected values of the fuel consumption of the SME is shown in Fig. 2 after processing a large amount of historical data related to the fuel consumption through MATLAB software. Also, the crew has a perceptual judgement on how to reduce the fuel consumption of the ship based on his own experience of navigation. What's more, the crew can gradually adjust the strategy in the actual operation, so that the overall fuel consumption of the ship is close to the minimum level. In other words, based on the analysis and summary of historical data, the curve consisting of the expected values of the fuel consumption of the SME, which is shown in Fig. 2, is an ideal fuel consumption curve.

Ship sailing fuel consumption is concerned by a lot of factors, some of which are caused by the ship itself, such as the oil pollution at the bottom of the ship, the difference value of draft, *etc.*, and the other part results

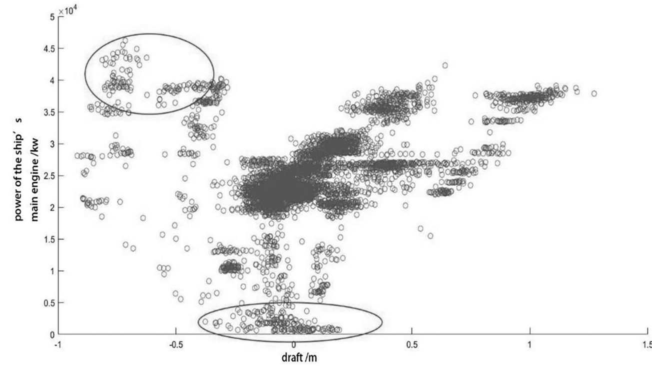

Figure 3. Relation between the power of the ship's main engine and the difference value of draft.

from the changes in the external environment, such as the wind speed, the wave height, *etc.* Fig. 3 shows the relation between the power of the ship's main engine and the difference value of draft. Based on the distribution of points, especially the density of points, it can be seen from Fig. 3 that, in addition to the ship's special conditions marked by the red circle, the power of the SME is related closely with the difference value of draft. Besides, when the difference value of draft is greater than zero, the power of the ship's main engine changes more frequently. Generally, the draft is closer to 0 when the engine power is below $2.5{\times}10^4$ kw; otherwise, it hovers between 0 and 1. Fig. 4 represents a comparison between the different value of draft and the fuel consumption of main engine. The horizontal axis in Fig. 4 is the same as that of Fig. 1, indicating different navigational stages (A$\sim$K), and the vertical axis denotes the difference value of draft. According to the value difference between the top and bottom of these boxes, there is larger change in difference value of draft at the navigational stages (D, E, F, H) which have higher fuel consumptions in Fig. 1. However, at the navigational stages with lower fuel consumption, the change in difference value of draft become smaller. Besides, it also can be found that the difference value of draft is less than zero at the navigational stages with lower fuel consumption. Therefore, it can be concluded that the fuel consumption can be reduced through a trim by stern within a reasonable range.

The change in the speed of the ship during navigation has a crucial influence on the fuel consumption. Studies have shown that the fuel consumption of the ship per unit time is directly proportional to the cube of the speed [18], which is also well demonstrated by the data fit between the power of the SME and the ship speed. The scatter plot between the fuel consumption of the SME and the ship's speed is shown in Fig. 5. It can be clearly seen that the fuel consumption of the SME has a significant correlation with the ship speed. Moreover, the trend curve fitted in Fig. 5 indicates that the fuel consumption of the main engine is directly proportional to the cube of the ship speed. The change in the fuel consumption of the SME with the ship speed, which is shown in Fig. 5, also better verifies that energy savings and emissions reductions can be achieved through the slowdown of the SME. In addition,

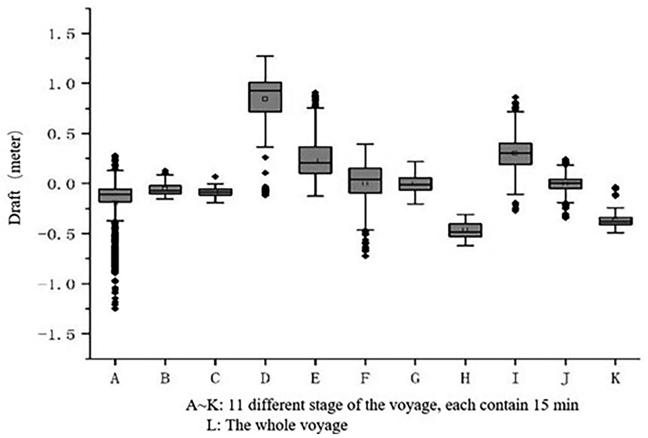

Figure 4. Comparison between the difference value of draft and the fuel consumption of main engine.

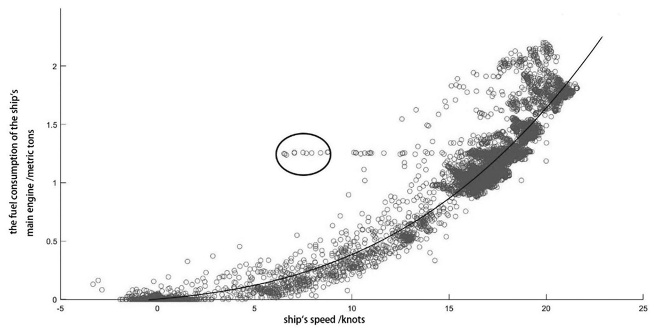

Figure 5. Scatter plot between the fuel consumption of the SME and the ship speed.

it can also be seen from Fig. 5 that there is still some special data, such as the data marked by a black circle, indicating that there is still obvious high fuel consumption at lower ship speeds. Wei explained in [23] that a long-term voyage under the condition that the main engine slowed down would result in excessive carbon accumulation in the main engine, which would cause some damage to the main engine. Also, owing to the need to eliminate the waste carbon inside the diesel engine by increasing the power, high fuel consumption can occur at low ship speeds.

4. Prediction Model of the Fuel Consumption of Main Engine Used in the Ship

4.1 Traditional Model Used for Predicting the Fuel Consumption

In order to verify the accuracy of this paper's prediction of fuel consumption of vessel main engine by using voyage data, the traditional model is firstly adopted to forecast the fuel consumption of the SME. The traditional vessel main engine fuel consumption prediction model adopts the same method as that in literature [18] and [19]. The traditional method used for predicting the fuel consumption of the SME mainly relies on the principle of ship propulsion, and there are many mature studies in this respect. Although the above-mentioned models [18] and [19] used for the speed optimisation are aimed at economic profit, the fuel consumption prediction in the model has clear objectives and actual environmental conditions in navigation are considered. Therefore, the predicted result of this model can be used to compare with that based on the voyage data. The traditional vessel main engine fuel consumption prediction is given as the following:

$$E = \frac{L_i}{v_i} \cdot (K_{\text{main}} \cdot P_{\text{main}}) \tag{1}$$

$$P_{\text{main}} = K \cdot (P_s + P_w + P_a) \tag{2}$$

$$P_s = \frac{\rho \cdot C_{\text{ts}} \cdot S \cdot v_i^3}{2} \cdot \left[\frac{M \cdot n}{\text{DWT}} + (n-1)\right] \tag{3}$$

$$P_w = \frac{\rho \cdot C_w \cdot g\left(H_{1/3}/2\right)^2 \cdot B}{L} \cdot (v_i + u) \tag{4}$$

$$P_a = \frac{C_a \cdot \rho_a \cdot A \cdot (v_i + u_a)^3}{2} \tag{5}$$

$$K = \max\left[\frac{1}{\eta \cdot \left(\alpha + \beta \cdot \sqrt{v_i/V_d}\right)}, \frac{1}{\eta\left(1 - r \cdot H_{1/3}\right)}\right] \tag{6}$$

where E, L_i, v_i, and K_{main} are the fuel consumption of main engine, the navigational stage, the ship speed, and the fuel consumption ratio of main engine, respectively; P_{main}, K, P_s, P_w, and P_a are the power of main engine, the propeller propulsion efficiency, the still water power, the additional power for wave resistance, and the additional power for air resistance, respectively; ρ, ρ_a, C_{ts}, C_w, and C_a are the density of water, the density of air, the still-water drag coefficient, the drag coefficient for the wave resistance, and the drag coefficient for the aerodynamic, respectively; S, M, DWT, $H_{1/3}$, B, L, and A are the wetted surface, the cargo on board the vessel, the maximum weight the vessel can carry, the wave height, the width of the ship at the waterline, the length of the ship at the waterline, and the surface area projected for the wind, respectively; u and u_a are the wave speed and the wind speed, respectively; η is the propulsion efficiency at the designed ship speed V_d, and the value of η ranges from 0.6 to 0.7; $\alpha+\beta=1$; r is a constant related to the wave.

Equations (2)–(6) are substituted into (1), and calculate the ship parameters mentioned in Part 3 into (1). Combined with the actual navigation conditions of the ship, the calculation results are shown in Table 1 and Fig. 6.

It can be seen from Table 1 and Fig. 6 that the traditional model has a certain accuracy in the fuel consumption prediction, which is close to the real fuel consumption. However, there is still a large error between the predicted value and the actual value, and the maximum error is above 0.12 metric ton. Also, the change trend of predicted fuel consumption is basically unable to reflect that of actual fuel consumption.

4.2 Evaluation of the BP Neural Network Model for Predicting the Fuel Consumption of an SME

The BP neural network has been widely used in data prediction, and is mainly used in model recognition and

Table 1
Some Results Predicted by the Traditional Method.
(Unit: metric ton)

η:0.6~0.7	$\alpha+\beta=1$	$r=$ c
Actual value	Test value	Absolute error
1.035608	1.0286	0.007008
1.023861	1.0236	0.000261
1.026384	1.0107	0.015684
1.02298	1.0255	0.00252
1.013612	1.0243	0.010688
1.005018	0.9981	0.006918
1.01745	0.988	0.02945
1.015087	1.0118	0.003287
1.021228	1.0528	0.031572
1.025952	1.0586	0.032648
1.014349	1.041	0.026651
1.003827	1.0114	0.007573
1.004689	1.0258	0.021111
1.023027	1.0562	0.033173
1.023866	1.1001	0.076234
1.018245	1.1102	0.091955
1.018983	1.0863	0.067317
1.039735	1.0194	0.020335
1.026735	1.0196	0.007135
1.028876	0.9833	0.045576
1.044024	0.9438	0.100224
1.052271	0.9281	0.124171
1.043844	0.9475	0.096344
1.038439	0.9609	0.077539
1.046755	0.9755	0.071255
1.038049	0.961	0.077049
1.047266	0.9894	0.057866
1.05005	1.0074	0.04265
1.035915	0.9915	0.044415
1.032749	0.9805	0.052249
1.046347	0.9586	0.087747

classification, time series prediction, function approximation, data compression, and so on [20]. The BP neural network can continuously correct the network weights and thresholds through the training of the sample data, so that the error function decreases in the direction of the negative gradient, thereby obtaining an output that approximates the desired. Zhou and Guojun demonstrated in 2016 that the BP neural network could be continuously corrected through the error backpropagation training, and could autonomously learn the mapping relationship between a large number of inputs and outputs, and could predict output according to input without giving a function relation in advance [21]. Therefore, as long as there is the reasonable data set as a prerequisite for network learning and training, a good predicted result of the fuel consumption of the SME can be obtained through the BP neural network.

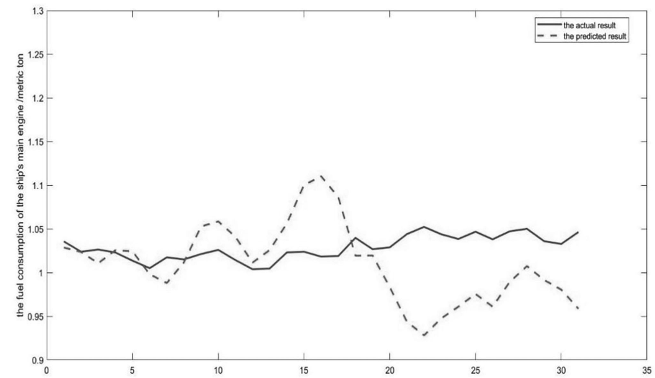

Figure 6. Comparison between the actual result and the predicted result obtained by the traditional method.

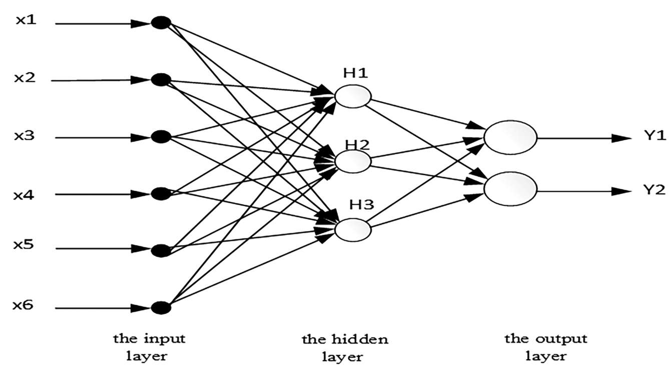

Figure 7. Neural network structure.

4.2.1 Network Structure Designing

In the neural network structure shown in Fig. 7, the left side is the input layer for inputting known measurements. The input layer of the BP neural network for predicting the fuel consumption of the SME has 20 units, including most of the data collected during the voyage of the ship, such as the power of main engine, the ship speed, the difference value of draft, the wind speed, the relative wind direction, the rudder angle, *etc.*

The middle part of the neural network structure is called the hidden layer, and the appropriate selection of the number of units in the hidden layer contributes to the prediction of accurate results [22]. The number of hidden layers cannot be used too much or too little, too

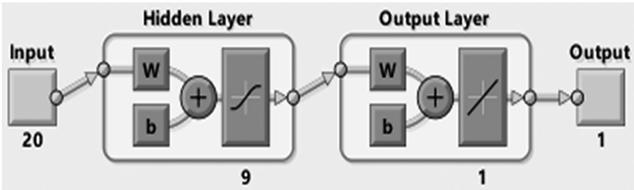

Figure 8. Neural network model.

little hidden layers may affect the accuracy of the model, and too many hidden layers may result in overfitting [23]. The number of hidden layer neurons generally depends on some empirical formulas, and the final determination of the number of neurons is based on some experience and several tests. In this paper, we refer to the following empirical formula when selecting the number of hidden layer neurons [30].

$$1 + \sqrt{n+m} + a \qquad (7)$$

where n is the number of neurons in the input layer, m is the number of neurons in the output layer, l is the number of neurons in the hidden layer, a is a constant in [1] and [10]. After several trial runs of the program, it was found that the effect of 9 neurons in the hidden layer was the best.

The right side of the neural network structure is called the output layer, which is used to obtain the results to be discussed in this paper, *i.e.*, the fuel consumption prediction of the SME.

4.2.2 Selection of Excitation Function and Model Implementation

The Neural Network Toolbox in MATLAB is employed to train the network, and the specific implementation steps are shown in Fig. 8.

The neural network model in Fig. 8 mainly includes the following four implementation steps:

a. *Normalisation:* Owing to the wide variety of big data related to voyage, the non-uniform dimension, the large changes in values, *etc.*, the data normalisation must be done before neural network training. Also, this paper normalises the data to [0, 1].
b. *Network parameter:* The default is netsum (weight as a coefficient, then sum).
c. *Network function:* The default in the hidden layer is sigmoid, and the default in the output layer is purein.
d. *Denormalisation:* The amplification ratio is determined by the training set, and the obtained results are reversely normalised to those with the same dimension as the original data.

4.2.3 Analysis of Predicted Results of BP Neural Network

Through neural network training, the data collected by ship sailing in a period are selected. In order to better reflect the learning and prediction of the original voyage-related big data, all the data in the input layer has been denoised by Kalman filter. Besides, the selected data set can show the sailing characteristics of the ship, including the above-mentioned data, such as the power of main engine, the ship speed, the difference value of draft, the wind speed, the relative wind direction, the rudder angle, *etc.* In the design of the network, the data collected on the last day of the ship navigation is selected as the test set. In addition to using the data of the test set as a training set for the neural network, this paper predicts the data of the last day of the ship voyage, and compares the data of the prediction set with that of the test set. The results obtained by the neural network training are shown in Fig. 9 (the predicted data vs. the actual data), Fig. 10 (the error of BP neural network), and Fig. 11(the regression analysis of BP neural network), respectively.

It can be seen from Fig. 9 that the relative error of the prediction result is small. Besides, in the variation curve of the error iteration in Fig. 10, the preset error is achieved after two iterations of all neural network training. In the regression analysis of the BP neural network in Fig. 11, the multiple correlation coefficient is more than 0.99. From the comparison between the predicted result and the actual result in Fig. 9, it can be clearly seen that the error of the predicted result at several points is large. It is also known that the main engine's fuel consumption at a point where there is a large error is usually less than 0.5 metric ton, and the error of the predicted result at the point where the actual fuel consumption is closer to zero is much larger. The actual fuel consumption is very low or even close to 0, indicating that the SME is running under very low load or even shut down. The special working conditions of the ship, and the large noise of the original data set can cause large errors. It can also be seen from Fig. 9 that the predicted result is very good and the error is the lowest when the fuel consumption of the SME is about 1 metric ton. In order to better evaluate the accuracy of the fuel consumption prediction of the SME, the difference in the weight of the crude oil consumed was used as an evaluation of the predicted result, as shown in Table 2. It can be seen from Table 2 that the maximum value of the absolute error is 0.07403 metric ton. After calculation, it is found that the average absolute error of all predicted results is 0.0153 metric ton, which is close to 15 kg. Since the fuel consumption of the ocean ship is mainly concentrated in 1∼1.5 metric tons/15 min, as shown in Fig. 1, these errors are not particularly noticeable compared to the huge fuel consumption of ocean ship.

4.3 Comparative Analysis of Two Models

The advantage of the BP neural network model based on voyage data is that the processing is simple and there is no complicated calculation. Besides, the complex voyage conditions of the ship can be reflected in the data through the in-depth learning of data. What's more, computer processing can save a lot of manpower and material resources. In addition, the fuel consumption predicted by the BP neural network is more accurate. The comparison between the relative error of the traditional method and that of BP neural network is given in Fig. 12. It can be seen from Fig. 12 that the relative error of the fuel

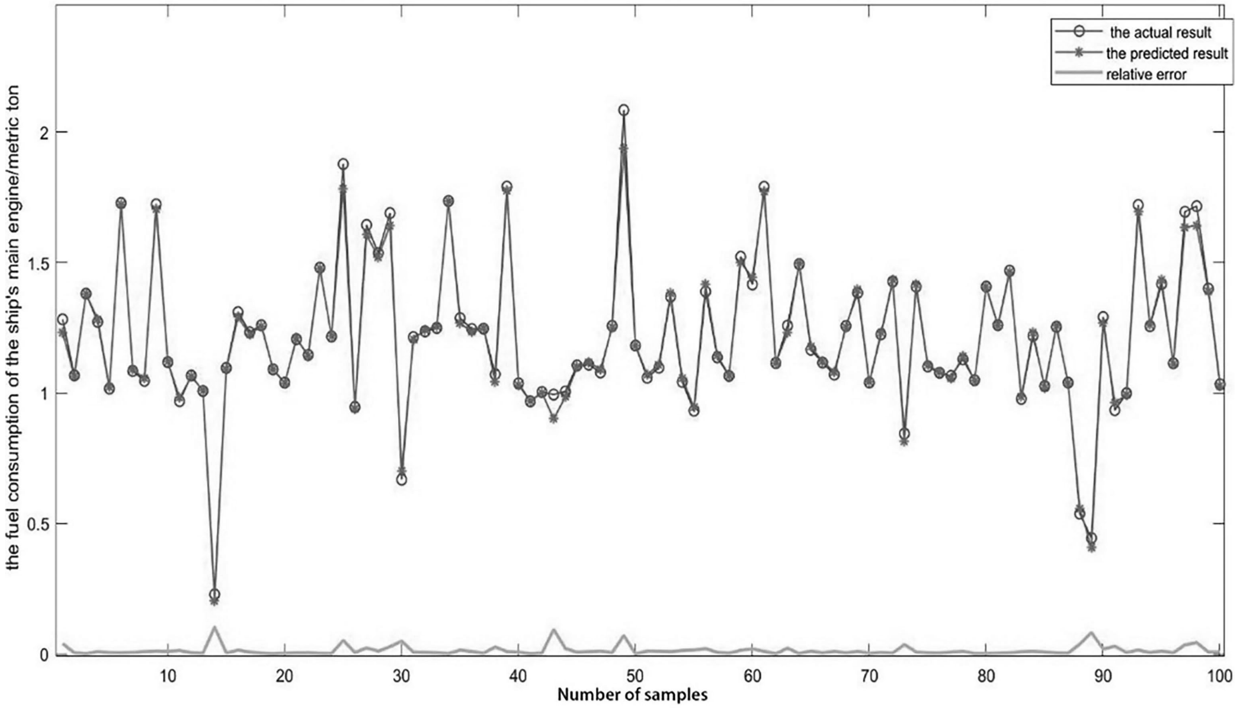

Figure 9. Predicted result vs. actual result.

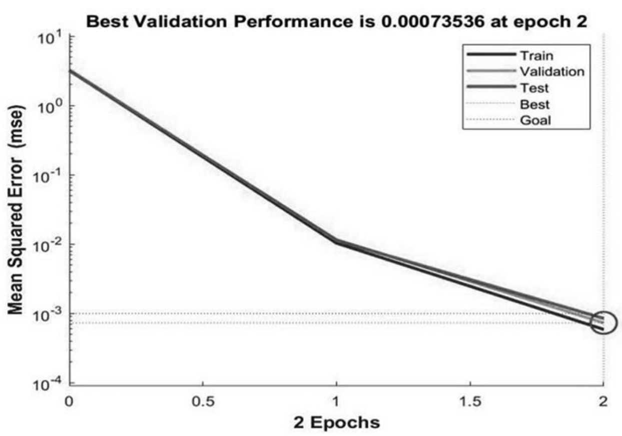

Figure 10. Error of BP neural network.

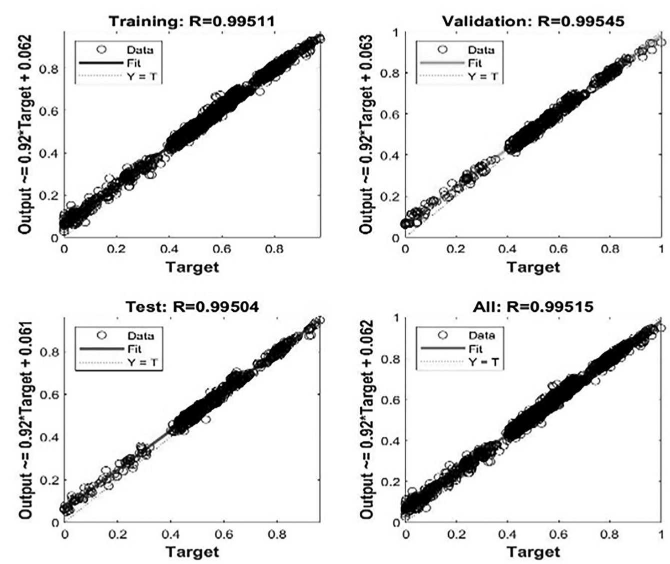

Figure 11. Regression analysis of BP neural network.

consumption predicted by the traditional model is large, and only a part of the predicted fuel consumption can match the actual fuel consumption. However, the relative error of the BP neural network model based on voyage data is generally smaller than that of the traditional model. It can also be seen from the comparison between Figs. 6 and 9 that the traditional model not only has lower prediction accuracy, but also cannot reflect the actual change trend of the ship's fuel consumption. Only a small part of the results predicted by the traditional model can approach the actual results, and the sea conditions and weather encountered in the actual navigation of the ship cannot be accurately reflected in the predicted fuel consumption of the SME. On the contrary, the BP neural network model based on voyage data can better reflect multiple factors, such as sea conditions, weather, *etc.* Besides, the predicted results obtained by the BP neural network model not only have a trend that is consistent with the actual fuel consumption, but also have a high accuracy, which can lay the foundation for more in-depth research on the ship's fuel consumption management.

Also, there are still some backwards.

5. Conclusions

This paper accomplishes a visual analysis and prediction of the fuel consumption of the SME. The significance of the visual analysis of the fuel consumption of the SME is

Table 2
Comparison Between the Partial Predicted Fuel Consumption and the Actual Fuel Consumption. (Unit: metric ton)

multiple correlation coefficient > 0.99		maximum absolute error = 0.07403	
Actual Value	Predicted Value	Relative Error	Absolute Error
1.407731	1.405537	0.001559	0.002194
1.260107	1.256782	0.002639	0.003325
1.468772	1.463358	0.003686	0.005413
0.977483	0.985451	0.008151	0.007968
1.219037	1.231867	0.010525	0.01283
1.026602	1.019411	0.007005	0.007192
1.253782	1.25819	0.003516	0.004408
1.039518	1.036665	0.002745	0.002853
0.537175	0.557362	0.03758	0.020187
0.443745	0.407474	0.081738	0.036271
1.291069	1.267149	0.018528	0.02392
0.934356	0.961772	0.029343	0.027416
0.998807	0.993601	0.005213	0.005206
1.720573	1.694954	0.014889	0.025618
1.256068	1.262148	0.00484	0.00608
1.417628	1.433107	0.010919	0.015479
1.113715	1.109106	0.004139	0.004609
1.694604	1.635535	0.034857	0.05907
1.716054	1.642024	0.043139	0.07403
1.399841	1.389802	0.007172	0.010039
1.033033	1.025865	0.006939	0.007168

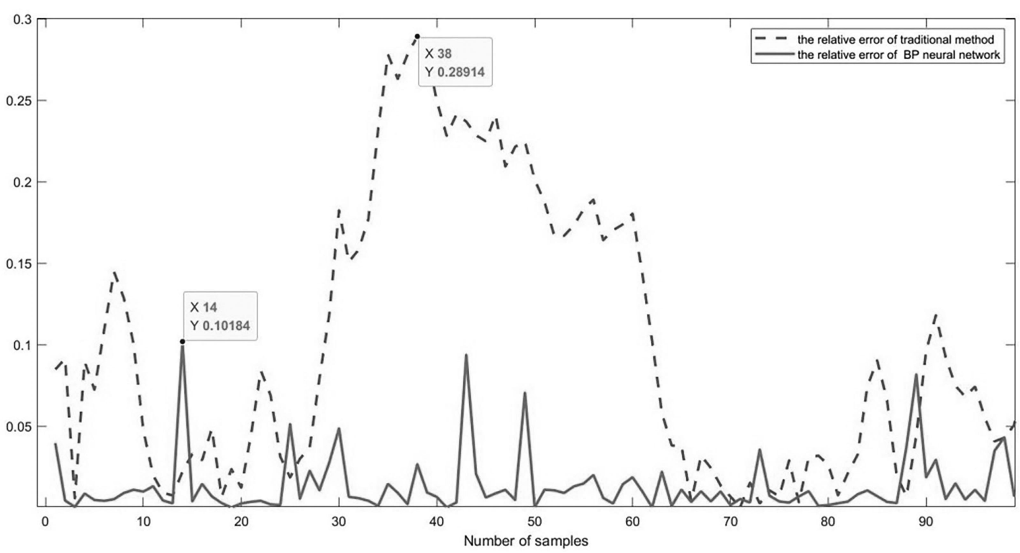

Figure 12. Comparison between the relative error of the traditional method and that of BP neural network.

that it can intuitively reflect the fuel consumption range of the main engine used in the ship during navigation, and some factors affecting the fuel consumption of the SME. Moreover, it not only helps to select a more suitable data type as the training set of BP neural network but also facilitates further research on the fuel consumption management of the SME. Although such methods have some drawbacks, particularly in terms of the regression model's interpretability, the shipping industry and relevant data sources will require more accurate and efficient regression models in the future as multivariate sea state data becomes more complex, allowing for interpretation and feedback.

This paper chooses the BP neural network model to predict the fuel consumption of the SME, which differs greatly from the traditional fuel consumption prediction method based on the principle of ship propulsion. A large number of the voyage data without denoising is selected as the training set of a BP neural network model. The advantage is that the voyage data without denoising covers all the conditions encountered by the ship during navigation. Also, the neural network training is completely data-based. Moreover, the fuel consumption of the SME can be accurately predicted without the complicated calculation of the traditional model. Therefore, compared with the traditional model used for the fuel consumption prediction, the BP neural network model based on voyage data is more advantageous. In addition, the BP neural network model is more in line with the actual requirements of the shipping company, so that it can provide an important basis for the shipping company to conduct reasonable voyage management and fuel consumption management.

Acknowledgements

The work presented in this paper is partially supported by Chongqing Municipal Science and Technology Commission Basic Research and Frontier Exploration Project (NO. cstc2016jcyjA0561), Chongqing Social Science Planning Project (NO. 2021NDYB077), Chongqing Postgraduate Joint Training Base Project (NO. JDLHPYJD2020030). This publication reflects only the authors' views . The authors would like to also acknowledge the assistance of the shipping company and consultancy firm that provided the data tilized in this study.

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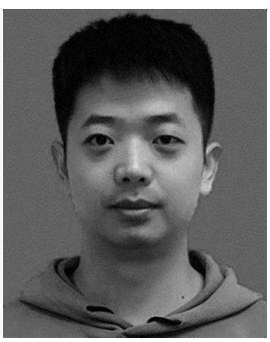

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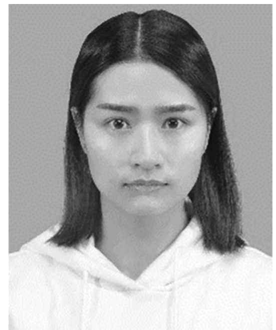

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