Data-aware monitoring method for fuel economy in ship-based CPS

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Abstract: With the acceleration of economic globalisation and the rapid development of network communication technology, remote monitoring and the management of ship fuel consumption have received extensive attention. Traditional fuel consumption monitoring methods are difficult to meet the growing management needs of the shipping industry due to problems such as large statistical errors and delayed information feedback. In order to better conduct energy management, equipment condition monitoring, and navigation analysis, the cyber-physical system (CPS) is deployed on ships to collect shipping data and communicate with remote monitoring centres. However, complex actual sailing conditions, sailing weather and other external factors tend to reduce the accuracy of fuel consumption data. In view of this challenge, a data-aware monitoring method for fuel consumption in ship-based CPS, named DMM, is proposed in this study. Technically, the fuel consumption index of ships is introduced firstly. Then, a fuel consumption model based on CPS is proposed, which improves the current fuel consumption model of the ship. Furthermore, the artificial neural network is employed to analyse a large amount of navigation data to get more accurate monitoring results of fuel consumption. Finally, experiments are conducted to verify the effectiveness of the authors’ proposed method.

1 Introduction

Nowadays, as the process of economic globalisation accelerates, trade between companies from all over the world is booming. Commodities among countries enter the markets of other countries through various channels, bringing novel goods to the people of other countries [1]. However, the long-term logistics costs also lead to high prices of imported goods, resulting in low sales. To reduce the cost of logistics, shipping has become the main way of world trade goods transportation. However, in the process of long-distance shipping, there are still some serious problems in ship management, especially in ship fuel management (e.g. insufficient fuel preparation) [2]. As the main power source of the ship, any problem in the fuel management of the ship may lead to the shutdown of the ship, thus causing irreparable losses for enterprises [3].

Furthermore, at the 69th meeting of the Maritime Environment Protection Committee (MEPC), ships with a gross tonnage of 5000 tons or more are required to collect data on each fuel consumption and other additional regulatory data [4]. In addition to the International Maritime Organization (IMO) request to record and report ship fuel consumption data, the EU’s Monitoring Reporting Verification (MRV) also sets new standards for ship fuel consumption data reporting. So in the next few years, the mandatory transition period of the ship fuel consumption monitoring mode will be ushered in [5]. In order to meet this requirement, the ship management department must adapt to relevant standards and requirements as soon as possible to innovate the existing ship fuel consumption monitoring and management.

Cyber-physical system (CPS), as a multi-dimensional complex system integrating computing, network and physical environment, plays a key role in many fields (e.g. health care, manufacturing, and modern logistics, etc.) [6, 7]. CPS empowers physical devices with computing, communications, remote coordination, and autonomy by connecting them to the Internet [8, 9]. Meanwhile, fuel management needs to be carried out by manually checking fuel-related instruments on the ship, which leads to the very low efficiency of fuel management and brings safety risks for the ship to carry out ocean-going missions [10]. Therefore, through the establishment of fuel consumption in ship-based CPS (SCPS), ships carrying out ocean-going missions can execute effective fuel management and facilitate land managers to conduct real-time analysis on the fuel use of ships, thus effectively reducing the risk of fuel shortage of ocean-going ships [11, 12].

In general, with the help of SCPS, the fuel of ocean-going ships is effectively managed. On the one hand, effective fuel management can enable ship maintenance personnel to obtain the state of surplus fuel in time, so that ship maintenance personnel can timely replace the fuel of the ship in time to ensure that the engine of the ocean-going ship can be in good working condition [13, 14]. On the other hand, the main cost of the ocean-going ship comes from the use of fuel, and the effective management of fuel can reduce the cost of performing ocean-going tasks to a certain extent.

However, the current SCPS does not take the actual sailing conditions, sailing weather and other external factors into account, which results in low accuracy of fuel consumption monitoring data. Moreover, the existing SCPS lacks an analysis of fuel consumption for historical voyages. Therefore, obtaining accurate fuel consumption data and using historical fuel consumption data to improve the accuracy of SCPS fuel consumption monitoring remains a key challenge. To addressing this challenge, a data-aware monitoring method for fuel consumption in SCPS is proposed in this paper. Specifically, the contributions of this paper are as following:

- An improved fuel consumption model in SCPS is established. By means of this model, the parameters related to the fuel consumption of ships are collected, and the fuel consumption of ships is judged and processed.
- The ship fuel consumption monitoring and management system consisting of server, user monitoring, shipborne terminal and fuel consumption data collection network is constructed.
- An artificial neural network (ANN) based method for fuel consumption of ships, named DMM, is proposed, which can...
accurately predict the real-time fuel consumption of ships and promote the supervision of fuel consumption of ships.

• A large number of experimental results obtained by performing multiple experiments with a real ship instance prove the effectiveness of DMM.

The rest of the paper is organised as follows. Section 2 analyses the fuel consumption indexes and proposes the fuel consumption model in SCPS. A data-aware monitoring method for fuel economy in SCPS is established in Section 3. Section 4 evaluates the performance of our method DMM and compares it with the traditional method CPF. Section 5 sums up the related work and presents future work.

2 Fuel consumption model

During the navigation process, the various navigational environmental parameters collected by the SCPS are affected by subjective and objective factors (e.g. navigation conditions and technical personnel operation level). As a consequence, it is necessary to analyse the collected data to determine the relationship between them and the fuel consumption of ships. In this section, fuel consumption indexes of the ship are introduced firstly, and then the instantaneous fuel consumption model of the ship is calculated to determine whether the fuel consumption of the ship is normal. Finally, aiming at the deficiency of the current marine fuel consumption model, a fuel consumption model in SCPS is proposed.

2.1 Fuel consumption indexes of ship

The management of ship fuel consumption is a basic responsibility of the shipping industry and other departments, and it is also a complicated task with diverse influencing factors. The thermal efficiency of fuel equipment (in the form of kilograms per hour) is the focus of early shipping companies. Afterwards, to meet the needs of enterprise management, the management departments calculate the actual load per thousand tons/km unit consumption on schedule, with the purpose of illustrating the change of fuel cost, rather than replacing the evaluation on the unit consumption per thousand horsepower/hour or the enterprise. In the late stage, the enterprises restored the fuel consumption management, since the enterprise management emphasised the economic benefit, plus the thousand horsepower/hour unit consumption this index form itself has some drawbacks, the quota form from thousand horsepower/ hour unit consumption gradually changed to the actual load thousand tons/kilometre unit consumption (i.e. economic fuel consumption).  

At present, the calculating method of fuel consumption in China is mainly divided into two forms: Marine vessel and inland river vessel. In addition, it is stipulated that there is no wind and waves in the navigation area, the vessel is fully loaded, and the standard fuel oil specified by the machine is used. Under the condition that the fuel quality remains unchanged, the calculation methods of fuel consumption indexes are as follows: The fuel consumption generated by the marine ship consists of the main engine, generator and boiler. The fuel consumption of marine vessels is calculated by the following formula:

\[ Q = Q_1 + Q_2 + Q_3 \]  

where \( Q \) represents the fuel consumption of the ship during operation. \( Q_1 \) represents the fuel consumption level corresponding to the main engine. \( Q_2 \) represents the fuel consumption level corresponding to the genset part. \( Q_3 \) represents the fuel consumption corresponding to the boiler fuel level.

The fuel consumption of the inland river ships is calculated as follows:

\[ Q = Q_1 \times t + A + Q_2 \]  

where \( Q \) is the fuel consumption of the voyage. \( Q_1 \) is the basic fuel consumption per hour. \( t \) is the standard sailing time of the voyage. \( A \) represents the unit turnover plus fuel consumption per kilometre. A represents the actual conversion turnover rate of the voyage. \( Q_2 \) represents the auxiliary fuel consumption.

In general, the evaluation index of the fuel consumption of ships is mainly divided according to the marine power plant, without considering the influence of many complicated factors (e.g. navigation parameters and navigation environment) on the energy consumption of ships.

2.2 Instantaneous fuel consumption index of ship

Since the average fuel consumption result from conventional SCPS is difficult to identify the abnormal events of ship fuel consumption, this paper measures the instantaneous fuel consumption of the ship based on accuracy measurement technology and real-time communication technology. Ship speed, ship energy efficiency, ship handling and other factors are directly related to fuel consumption. Determine the different manifestations of the ship's fuel consumption, so as to be able to understand the ship's fuel-saving state under what operating conditions, and how to adjust the ship to fuel-saving state. Since the auxiliary power consumption of the ship is relatively balanced, by monitoring the main engine fuel consumption, navigation parameters of the ship could be applied to help correct the data is corrected directly.

The effective fuel consumption rate of a diesel engine, \( u_{fe} \), refers to the fuel consumption per kWh of effective power in kilograms per kWh (kg/kW·h). The minimum fuel consumption rate is the ship's speed when the minimum fuel consumption rate of the diesel engine is maintained. The fuel consumption rate of diesel engines is usually affected by factors such as fuel injection quantity, ventilation quality and speed. According to the working form and usage of diesel engines, the minimum fuel consumption rate of marine diesel engines is usually between 90 and 100%. When discussing the needs of various power reserves in the process of proposing, for the diesel engine operating under the propulsion state of the ship, the \( u_{fe} \) (effective fuel consumption rate) value is usually the smallest at 85% load, and the change is shown in Fig. 1.

In Fig. 1, P is the calibration power of the diesel engine, SFOC (Specific Fuel Oil Consumption) represents the fuel consumption rate of the ship, and ΔSFOC represents the amount of change in the fuel consumption rate of the ship. It is obvious that the diesel engine has the lowest fuel consumption rate under the operating state of the \( u_{fe} \) minimum, and the diesel engine has the best economy. The speed of the ship at this time is the lowest fuel consumption rate.

2.3 Fuel consumption model of ship based on empirical formula

The fuel consumption model of the ship mainly includes the relationship between the host fuel consumption and the parameters such as the speed of the ship and the speed of the host. The fuel consumption model of ship can optimise the navigation route according to the trajectory of the ship's navigation and the time of

![Effective fuel consumption curve of the diesel engine](http://creativecommons.org/licenses/by/3.0/)
The existing fuel consumption model based on the empirical formula mainly shows that the calculation relationship between fuel consumption and speed is derived based on the matching relationship between ship, machine and paddle, and the route is simplified by segmentation. The treatment, under the condition of considering the entire range, optimises the speed of the flight segment, so as to optimise the whole navigation process and construct the optimal scheduling model. The accuracy of this kind of optimisation model based on the theoretical formula is improved, which can provide a reference for the establishment of most fuel consumption models of ships. The theoretical formulas or related parameters are selected reasonably for different ship types to optimise the model. However, this type of model basically only selects some influencing factors for analysis and research, which is not comprehensive enough, and ignores the possibility that each factor has mutual influence.

### 2.4 Fuel consumption model in SCPS

Fuel consumption of ship is mainly determined by the ship's main engine, ship auxiliary equipment and the other equipment, but there are still many factors that affect fuel consumption, such as ship navigation conditions, ship type and structure, hull resistance, ship life, cargo load, sailing speed and the operation of driver, etc. The ship fuel consumption collection proposed by IMO is a fuel consumption decision-making activity supported by big data technology. In order to determine the conditions under which the ship is in a fuel-saving state, how to adjust to the fuel-saving state, it is necessary to areas and types of ship fuel consumption are investigated, statistically analysed and analysed to determine the factors affecting ship fuel consumption. Based on this, a fuel consumption model in SCPS is proposed to calculate the fuel consumption accurately. To more clearly describe these influencing factors, these factors can be divided into oil-machine-environment systems and represented by the structure shown in Fig. 3.

However, from a practical point of view, it is difficult to accurately measure fuel consumption by monitoring fuel flow and calculations in a single way. Therefore, according to the parameter values related to the collection of ship and fuel consumption, data processing technology is used to judge and data the ship's fuel consumption value, so as to obtain more accurate fuel consumption, that is the fuel consumption of the main engine is measured, and the ship's navigation parameters are used to assist the correction.

In the SCPS, each subsystem actually has a coordinated effect on fuel consumption. In order to adapt to the diversity of fuel consumption data, it is necessary to flexibly change the sampling frequency of the parameters in the fuel consumption monitoring mode and adjust the correlation between the data parameters. Let the number of subsystems of the system be \( m \), use \( Q_i \) to indicate a certain parameter in the system. That is, the impact of the subsystem on the fuel consumption of the ship. Due to the relevance of the system, any \( Q_i \) will be affected by \( Q_i \) to \( Q_m \), so it is all function of \( Q \). Similarly, any \( Q_i \) will be affected by all other \( Q_i \) and systems. This effect can be expressed by (3). According to different fuel consumption monitoring methods, select \( n \) subsystems to form (4), and the steady-state of the system. It is characterised by the disappearance of the changed \( dQ/dt \) and can be described by (5)

\[
\begin{align*}
\frac{dQ_1}{dt} &= f_1(Q_1, \ldots, Q_m), \\
\frac{dQ_2}{dt} &= f_2(Q_1, \ldots, Q_m), \\
&\vdots \\
\frac{dQ_n}{dt} &= f_n(Q_1, \ldots, Q_m).
\end{align*}
\]
The fuel-machine-environment parameters mentioned in this section are reflected in (3)–(5), where each system $Q_i$ is affected by a variety of parameters. Equation (5) has multiple sets of solutions, representing several states of the system, which is the mathematical model for calculating the fuel consumption of the ship. The whole system is in a stable state when the number of guidance is zero. It can be seen that the parameters of the ship fuel consumption monitoring and acquisition are mutually coupled, and the appropriate acquisition accuracy and frequency must be selected according to the correlation between the parameters and can be adjusted in real-time.

It can be seen that the ship fuel consumption model based on the empirical formula is used to monitor the ship's fuel consumption mode is too single, without considering the complex working conditions of the ship and the influence of environmental factors. The fuel consumption model in SCPS is more accurate and efficient than the model introduced by the empirical formula.

3 Data-aware monitoring method for fuel economy in SCPS

As we discuss in Section 2, a fuel consumption model in SCPS can analyse the impact of single navigation area environmental factors on fuel consumption. On this basis, to select the shipping area, optimise the speed of the ship and ensure the high energy efficiency of the ship, it is necessary to make real-time predictions of the fuel consumption of the ship. The environmental navigation factors and the ANN are employed to better predict the fuel consumption accuracy in this section. Firstly, the environmental navigation factors which affect the fuel consumption of the ship are evaluated. After pre-processing the actual fuel consumption data, the ANN is employed to train the sensor data to predict the real-time fuel consumption of ships.

3.1 Data preprocessing

The navigation data generated in multiple voyages are completely enormous and unable to be employed for analysis directly. Firstly, the singular values and noise data in the original datasets are eliminated and broken up into every 3 min. In the process of establishing the actual fuel consumption model of the ship, different types of data will be processed and integrated, and the measurement units and orders of magnitude between the ship fuel consumption and navigation factors (e.g. wind speed and ship speed) are also far away, making it impossible to conduct comparative analysis between these data. Therefore, data samples are processed dimensionless to solve the incomparability between typical navigable factors of fuel consumption of ships. The environmental parameters collected every 3 min are subjected to min–max standardisation to obtain the characteristic quantity of the data, which is determined by

$$\alpha_i = \frac{d_i - \min^i}{\max^i - \min^i},$$

where $\min^i$ represents the minimum value of all data samples in the $i$th data type in the three-minute duration, $i$ represents all navigational environmental factor data such as ship trim, and $N$ represents the number of all data samples in three minutes. $d_i$ represents the actual value of the $i$th data type in the $n$th data sample. $\alpha_i$ represents the normalised value of all samples in the $i$th data type after processing. After the min–max normalisation process, essentially, the data is scaled to dimensionless data, which converts the sample set into a small specific interval. These data can eliminate the order of magnitude difference between the factors.

3.2 Neural network-based dynamic fuel consumption model of ships

The ship navigable environment factors (e.g. navigation area characteristics, navigation area wind-wave grade and weather characteristics), which has a great impact on ship fuel consumption. The ANN is employed in this section to mine the relationship between the navigation factor and fuel consumption, which combine with the various navigation factor data in the actual navigation of the ship to achieve dynamic prediction of fuel consumption [15, 16]. The model of ship fuel consumption training in this paper adopts a three-layer fully connected neural network, the composition of the model mainly includes the following parts.

3.2.1 Input sample data: These datasets include the fuel consumption actually collected and the corresponding navigation factors, which have been converted into decimals between 0 and 1 after normalisation processing. And the dimensionless data have been transformed from dimensionless data through expressions, which helps simplify the operation and accelerate the training speed of the neural network [17, 18]. The processed data were divided into a training set and test set according to the proportion of 70% : 30%.

3.2.2 Input layer and output layer: The number of neurons in the input layer and the output layer should be changed according to the actual situation [19]. However, it is worth noting that the number of input layer nodes generally cannot be less than the number of dimensions of simulation or training sample vectors. Assuming that the above input layer has R-dimensional input, and $\{x_1, x_2, \ldots, x_R\}$ are used to represent the $R$ inputs, respectively, and the corresponding input vector can be represented by the $R^*1$-dimensional column vector $x$ (T represents transpose), which is measured by

$$X = [x_1, x_2, \ldots, x_R].$$

The purpose of employing the neural network is to obtain the relationship between the parameters of multiple navigation factors and the fuel consumption of ships, and to deduce the input characteristic vector to the final output layer through layers. The process of output prediction of fuel consumption is a typical regression problem. Therefore, the output layer has only one node, and the output value of a neural network is represented by $Y$.

3.2.3 Weights and thresholds: The weight of each layer in the neural network is represented by $w_{1}$ to $w_{k}$, and the network weight can be understood as the strength of the connection between each input vector and the neuron. If the input value is always 1, and the threshold of the neuron is expressed, then the threshold of the neuron can be represented by the network weight under the input condition. If a row vector is used to represent the network threshold of the neuron, which is measured by

$$W \equiv \left[ w_{1}, w_{1}, \ldots, w_{k} \right].$$

According to the dynamic change characteristics of the neural network, the network threshold and network weight should be changed, and it is precisely due to this dynamic characteristic that neurons and neural networks have various characteristics. In fact,
Table 1 Monitoring parameters datasets

| Filename               | Parameter description | Units |
|------------------------|-----------------------|-------|
| fuelDensity.csv        | fuel density          | kg/l  |
| fuelTemp.csv           | fuel temperature      | C     |
| fuelVolumeFlowRate.csv | fuel volume flow rate  | l/s   |
| inclinometer-raw.csv   | inclinometer trim angle | deg. |
| latitude.csv           | latitude              | null  |
| longitude.csv          | longitude             | null  |
| speedKnots.csv         | speed over ground (SOG)| km/h |
| speedKmh.csv           | speed over ground (SOG)| km/h |
| windSpeed.csv          | wind speed            | m/s   |
| starboardPitch.csv     | starboard propeller pitch | -10 to 10 V |
| starboardRudder.csv    | starboard rudder pitch | -10 to 10 V |
| windAngle.csv          | wind angle            | deg.  |
| trackDegreeMagnetic.csv| track degree magnetic  | deg.  |
| trackDegreeTrue.csv    | track degree true     | deg.  |
| trackHeading.csv       | true heading          | deg.  |

3.2.4 Structural design of the hidden layer: When training with a neural network, since any continuous function in the closed interval can be approximated by the network of a single hidden layer, there is a theorem that if the mapping from dimension to dimension is to be completed, it can be achieved by using a three-layer network. The number of hidden layer nodes is between the number of input nodes and the number of output nodes, and the convergence speed of the network is accelerated as the number of nodes approaches the input node. After comprehensive consideration, the following extreme formula for the number of hidden layer nodes is proposed:

\[ n_l = \begin{cases} n + 0.618 \times (n - m), & n \geq m, \\ m - 0.618 \times (m - n), & n < m. \end{cases} \]  

3.2.5 Activation function: The activation function is generally employed in each hidden node of the neural network. The weighted sum of the previous hidden layer is calculated by the activation function and input into the next hidden layer. The sigmoid function is adopted as the activation function in this paper, which is calculated by

\[ f(a_l^i(m)) = \frac{1}{1 + \exp(-a_l^i(m))}, \quad a > 0, \quad -\infty < m < +\infty, \]  

where \( a_l^i \) refers to the input of neuron \( l \) on the network \( L \) layer, \( a \) represents the constant.

3.2.6 Loss function and network optimisation: Our purpose is to accurately predict the real-time fuel consumption based on the data of various navigable factors through the training of the neural network. This kind of regression problem often needs to calculate the error between the actual fuel consumption value and the predicted value, which is also called loss. The most commonly used loss function is a mean squared error (MSE). It is defined as follows:

\[ \text{MSE}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2, \]  

where \( y \) represents the actual fuel consumption value in the test data, \( \hat{y} \) represents the fuel consumption value predicted from the test parameters, and \( n \) is the number of data samples. In order to further optimise training network, making efficiency and fuel consumption value more accurate prediction, the exponential decay method is adopted for the learning rate. This method is able to find the optimal solution faster at the initial stage of the algorithm’s operation if a higher learning rate is set in advance. Then, the algorithm can intelligently reduce the learning rate to make the searching process more stable at the end of the iteration. In the end, to avoid the over-fitting of the model, L1 regularisation method is adopted on the basis of the loss function.

4 Experiment evaluation

The proposed monitoring method for fuel consumption is evaluated in this section. Firstly, the monitoring parameters are configured and pre-processed. Then, a cubic polynomial fitting method is introduced for comparison analysis. Finally, the predicted and actual values of some test datasets are compared and the contrastive analysis for performance evaluation is undergone.

4.1 Experimental setup

The case ship employed in the experiment is the Brilliance 377 wheel, and the main route is the domestic coastal. The full-load tonnage of the ship is 3000 tons, the main engine model is X61 14ZC-33, the rated speed is 1350 r/min, and the rated power is 441 kW. The sensor is installed in different parts of the ship and used to collect various data during the operation. This paper uses the fuel consumption monitoring system to measure the running data of 52 rounds of the whole year. The main monitoring parameters are shown in Table 1.

4.2 Comparison method

To demonstrate the performance of our proposed method DMM, we contrast it with the existing methods, i.e. Cubic Polynomial Fitting (CPF) method. The key idea of CPF-based fuel monitoring is that the CPF is employed to establish the relationship between the parameters and fuel consumption of the ship.

4.3 Performance evaluation

The fuel consumption is equal to the product of the host output power and the fuel consumption rate. When the power and speed of a marine diesel engine changes, the fuel consumption rate changes due to the amount of fuel injection, the quality of the ventilation, and the speed of the ventilation. According to the ship, machine, and paddle matching relationship and previous research data, the host speed and fuel consumption are three times. Therefore, the ship fuel consumption model can be directly established by using three fitting equations. From the pre-processing data, the main navigational factors affecting fuel consumption are fitted and evaluated (including ship speed, water depth, wind speed, wind direction and host power).

4.3.1 Fuel consumption and speed: In this paper, the least square cubic polynomial fitting function is used to fit the fuel consumption curve to establish the relationship between speed and fuel consumption. In addition, according to the relationship between the ship, the engine and the oar, the fuel consumption per unit distance increases with the speed of the ship. As shown in Fig. 4, the fitting degree of DMM between predicted speed and fuel consumption was significantly better than that of CPF.

4.3.2 Fuel consumption and power: Using the pre-processed data, the fuel consumption rate is fitted three times to determine the relationship between the host output power and the fuel consumption rate, as shown in Fig. 5. According to the model, the navigation plan is relatively compact when the ship has a large number of navigation tasks, and the diesel engine is always in a high load state during the voyage.

The working point of a diesel engine at the lowest fuel consumption rate should be as close as possible to the actual situation. After adjustment, the fuel consumption of a diesel engine can be effectively reduced. As we can see from Fig. 5, the fuel consumption power curve fitted by DMM is more accurate than...
4.3.3 Fuel consumption and water flow speed: With the increase in water flow speed, the fuel consumption of the ship per kilometer increases sharply. Because the boat is travelling upstream, the speed is lower, and the fuel consumption per kilometre is increasing. The increase in water flow velocity directly leads to an increase in fuel consumption. The positive correlation between them also indicates that the ship is sailing against the current, which is consistent with the actual sailing conditions. The fitting relationship between water flow velocity and fuel consumption rate is shown in Fig. 6. As can be seen from Fig. 6, the fitting effect of DMM is significantly better than CPF.

4.3.4 Fuel consumption and wind speed: For the external influence factors of wind, the influence reflected in wind speed is positively correlated with fuel consumption. In general, the ships are sailing against the wind. When wind speed is <0.5, fuel consumption does not fluctuate with wind speed. When the wind speed is >0.5, the influence of wind speed factor on fuel consumption increases. The fitting relationship between wind speed and fuel consumption is shown in Fig. 7, and it can be seen that the fitting effect of DMM is significantly better than CPF.

4.3.5 Fuel consumption and wind direction: As the wind direction increases, the impact on fuel consumption is increasing. When the wind direction is >0.7, the influence of wind direction on fuel consumption is significantly increased. When the wind direction is 0–0.4, the wind speed has little effect on the speed of the ship and only fluctuates within a small range. The fitting relationship between wind direction and fuel consumption is shown in Fig. 8. It can be seen from Fig. 8 that the fitting effect of DMM is obviously better than that of CPF. And when the wind direction angle is around 0.4–0.7, the influence of wind on navigation is the biggest hindrance effect.

4.3.6 Fuel consumption and depth of water: Since the shallow water resistance rapidly decreases the water depth as the water depth increases, when the water depth of the channel is 0–0.3, the fuel consumption decreases rapidly as the water depth increases. When the water depth is >0.6, the water depth has little effect on fuel consumption. It can be seen that the water velocity factor is significant, and the water depth is negatively correlated with fuel consumption. That is, the greater the water depth, the smaller the ship resistance and the lower the fuel consumption. The fitting relationship between water depth and channel fuel consumption is shown in Fig. 9, the fitting effect of DMM is obviously more accurate than CPF.

4.3.7 Comparison of actual value and predicted value for fuel consumption: Based on the navigational environmental impact factors such as speed, water speed, water depth, wind direction, wind speed and host power, a static fuel consumption model based on typical environmental factors is established to achieve a quantitative analysis of the impact factors of navigation environment. However, in actual situations, ship navigation is often a cross-strait area and dynamic. In order to find out the corresponding minimum fuel cost and speed according to the specific conditions and navigation requirements of the diesel engine of the ship, and effectively guide the choice of the speed of ship, the accuracy of the fuel consumption model of ship must be further improved in combination with the actual data of the ship. The neural network will be used to further optimise the ship fuel consumption model.

The navigable factor is an independent variable, and the fuel consumption of the ship is a dependent variable. Randomly select 150 samples from the original sample as test samples. Using the established dynamic fuel consumption model of the ship to predict the fuel consumption of the sample data, and finally comparing the predicted value with the actual value, the predicted fuel consumption and actual fuel consumption of the BP neural network for the training sample are shown in Fig. 10.

Through the training of the ANN, the prediction of different fuel factors by the fuel consumption model can be seen from the 150 sets of test data randomly selected in the figure. The network predicts the fuel consumption value of the ship and the measured fuel consumption value have a high degree of coincidence. The following ten sets of data are randomly selected as test samples and input into the trained ANN model. The final calculation results of the system are shown in Table 2.
As shown in Table 2, the fuel consumption prediction model based on ANN constructed in this section has high prediction accuracy. It can be found from the statistical data that the absolute error between the predicted value of the fuel consumption prediction model and the actually measured fuel consumption value is 12.3367, the minimum absolute error is 0.8709, and the relative error of the remaining test data is small. The average deviation of the predicted values is about 6.23%, which means that the model can predict the fuel consumption value of the ship well.

### Table 2

| Sample number | Actual fuel consumption, kg/h | Predicted fuel consumption, kg/h | Relative error, % |
|---------------|-------------------------------|----------------------------------|-------------------|
| 1#            | 33.87                         | 32.56                            | 3.8               |
| 2#            | 47.51                         | 49.77                            | 4.7               |
| 3#            | 58.56                         | 64.19                            | 9.6               |
| 4#            | 67.38                         | 70.70                            | 4.9               |
| 5#            | 68.83                         | 69.84                            | 1.4               |
| 6#            | 80.26                         | 86.98                            | 8.3               |
| 7#            | 98.64                         | 110.98                           | 12.5              |
| 8#            | 88.37                         | 81.31                            | 7.9               |
| 9#            | 98.13                         | 89.76                            | 8.5               |
| 10#           | 122.85                        | 123.72                           | 0.7               |

5 Related work

The fuel consumption is a vital factor which influences the operating state of the running ship. Many procedures are dedicating to predict and control the ship fuel consumption [20–23]. A multiple linear regression-based model is proposed in [20] to achieve the use of speed–power curves in the Naval Architecture. This approach is employed to alert technical management of a ship fuel consumption, and to digitise the fuel cost-effectively. In [21], Bocchetti et al. designed a statistical approach that allows for both pointwise and interval predictions of the ship fuel cost. Aiming to accomplish the real-time assessment of fuel cost, an integrated fuel management system that achieves economically optimised and environmentally amity is presented in [22]. In [23], Yin et al. presented a new type of ship fuel cost monitoring system, which achieves real-time data monitor, e.g. oil cost, power generates and ship speed.

In the light of ever-evolving network communication technologies, the new approach of cyber fuel management is reaching the silver linings. As a multi-dimensional complex system combining network, computing and physical environment, CPS plays a key role in many fields [23–26]. Aiming to improve the convenience of healthcare, Zhang et al. presented a cloud and big data-based integrated CPS for patient-centric healthcare named Health-CPS [23]. Their work achieves that combine with cloud and big data service, then the performance of healthcare is much improved. In [24], Wang et al. discourse the present status as well as the latest development and application of CPS in manufacturing. They summarise the relativity studies and applications in CPS and show the potential and premise in the next generation of manufacturing. In order to keep up with the times, Zhang et al. [25] proposed an architecture that addresses the mechanism and solution of CPS and the Internet of Things based logistics systems. According to the experimental evaluation, the efficiency of this cyber logistics system is much improved. In the age of industry 4.0, Lee et al. [26] presented that any information generated by all disparate devices is monitored and transmitted through the high-speed internet from the physical hard devices to the cyber computational space. Riding with this advanced communication tool, the performance of connected things like ships will be far more efficiently, flexibly and collaboratively.

An SCPS can provide real-time monitoring and data management, real-time and efficient data collection and transmission, ship positioning, production scheduling, financial management and process integration of ship transportation industry [27]. According to Lee et al. [28], SCPS can effectively improve the modern management ability of shipping enterprises, improve the performance of fuel consumption, extend the service life of ships, improve the actual seaworthiness of ships, reduce operating costs, bring considerable economic benefits to shipping enterprises, and further improve the market competitiveness. Rajkumar et al. [29] presented that SCPS achieves information response timely, it does not only save fuel for the ship, but also realises the goal of saving resources, liberating manpower and improving efficiency. Therefore, SCPS has a broad application prospect and high application value. Ang et al. believe that the way we design and produce things must be evolving and adopting proactively [30–32], they presented one kind of smart framework design of the next-generation smart ships, which disclose the significance of the intelligent of ship fuel consumption. How to adopt the CPS into next-generation smart ships, accomplish the fuel conservation, is an urgent issue.

To the best of our knowledge, these previous works have limitations on the focus of data-aware as well as fuel economy when combining the ship with the CPS. A data-aware monitoring method is needed to meet the requirement of fuel economy in SCPS.
6 Conclusion and future work

To effectively manage the fuel of ocean-going ships and realize the condition monitoring and navigation analysis of the equipment on the ships, the CPS is deployed on the ships to collect the ship data and communicate with the remote monitoring centre. However, due to the complex actual sailing conditions, sailing weather and other external factors will often lead to the accuracy of fuel consumption data reduction. For addressing this challenge, an SCPS fuel consumption data sensing monitoring method, named DMM, is proposed in this paper. Besides, to improve the existing ship fuel consumption model, a fuel consumption model based on the ship oil engine-environment system is proposed. Moreover, the data collected by various fuel consumption related sensors on the ship are analysed by ANN to get more accurate fuel consumption monitoring results. Finally, the effectiveness of the method is verified by a large number of experiments.

In the future, we hope to apply the method proposed in this paper to CPS deployed on the real ocean-going ships.

7 References

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