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Research Article

A Novel Big Data Collection System for Ship Energy Efficiency Monitoring and Analysis Based on BeiDou System

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The call for green shipping is increasing, and the reduction of greenhouse gas emissions from ships becomes more and more important. Traditional ship energy efficiency monitoring is based on the noon reports, which are susceptible to human error and have a time delay. Many ship energy efficiency monitoring systems have been designed and developed, but they usually cannot send data to the shore in time. In order to identify abnormal fuel consumption in time, this paper realizes a big data collection system for ship energy efficiency monitoring based on the BeiDou System. The system installed on two sister container ships has already collected a lot of data. Big data analysis methods, such as principal component analysis (PCA) and correlation analysis, are applied in the system to realize data visualization and analysis. Using PCA, it turns out that the shaft power of the main engine is related to a certain ship speed, which is also affected by load and weather conditions, and is the biggest factor in determining fuel consumption. To realize the assessment of hull fouling and the optimization of ship trim, a useful physics-based analysis is proposed. The analysis shows that the fouling of ship body greatly increases its resistance. Our analysis method can also find the best trim under specific loading condition. All these points are important for reducing fuel consumption and improving ship efficiency.

1. Introduction

International shipping contributes to about 2.89% of the global man-made emissions of CO_2 averagely in 2018 [1, 2]. Meanwhile, the voice of green shipping is getting higher and higher. Reducing shipping carbon dioxide emissions has become a top priority. In order to reduce CO_2 emissions, the regulations regarding Energy Efficiency Design Index (EEDI) and Ship Energy Efficiency Management Plan (SEEMP) entered into force on January 1st 2013 [3, 4]. A new chapter—Energy efficiency management—was added to MARPOL Annex VI. Furthermore, a new mechanism of data collection system for fuel oil consumption of ships also came into force in 2018 to improve ship energy efficiency. Besides, the European Union regulation on Monitoring, Reporting, and Verification (MRV) started to monitor fuel consumption of ships having more than 5000 gross tonnage (GT) in 2018 [5].

While the pressure of greenhouse gas emission reduction is increasing, fuel cost is always a main cost for shipping. The importance of improving the efficiency of ships and saving fuel can never be disregardful. When a ship is sailing at sea, it needs to overcome the resistance of water, wave, and wind. Hochkirch and Bertram [6] introduced four aspects of fuel saving, including reducing ship resistance, improving propulsion efficiency, reducing fuel consumption of onboard equipment, and increasing recyclable energy. In terms of reducing ship resistance, optimized trim can change the shape of wet body of ship and result in resistance reduction, which has a potential of 5% fuel saving [6]. After the ship is put into use, its performance will decrease as the service time increases. Hull fouling is an important factor leading to the increase of resistance and fuel consumption [7]. It is reported that the fouling of ship hull can increase the resistance of the ship by about 25%–50% [8]. The prediction and treatment of hull fouling are essential for fuel saving. Therefore, proper and timely cleaning can significantly reduce fuel consumption and improve ship efficiency [6–9].

Ship energy efficiency monitoring can support data analysis, identify abnormal states of ship energy efficiency, and guide crew operation. Pedersen et al. collected three sources of data, which included the noon reports, measured data, and hindcast data of weather information [10]. Comparing linear, nonlinear, and artificial neural network (ANN) models, they found that ANN has the smallest fitting error. According to the empirical equation of fuel consumption, Yang et al. divided it into four piecewise functions: head sea, bow sea, beam sea, and following sea [11]. Genetic algorithm (GA) is applied to search for the coefficients based on the noon reports. The data come from 7-year noon reports including 1808 items of data, and only 1011 items are left after filtering. Based on the proposed fitting function, Ancona et al. [12] tried to optimize the energy load allocation by GA. Although they achieved the optimization goal, the work was based on manually recorded data. Using Gaussian process (GP) regression model, Yuan et al. fitted and predicted fuel consumption [13], but no special attention was paid to accuracy. Tran introduced a fuzzy hierarchy process to determine the importance of factors affecting fuel consumption [14]. In [15], the designed decision aid system based on the ANN model helps to optimize the ship trim and speed to save energy consumption. However, most of the above studies are based on the data of noon reports, which are full of uncertainty [16]. The shortcoming of noon reports can be summarized as follows.

(1) Human intervention may cause data errors. The energy data analysis does not work since the data are not correct.

(2) The noon reports get the data manually, which is time-consuming and laborious to do statistics.

(3) There are time delays if something goes wrong, and company management is weak.

(4) The amount of data is small and fails to meet the requirements of many analytical methods.

In order to overcome those shortcomings, a system that automatically records the ship's performance and efficiency needs to be designed and installed on the ship. Recently, many shipping companies have designed and developed a number of different ship energy efficiency monitoring systems. Chris-Marine has developed a Ship Performance Efficiency Analyzing Tool (SPEAT) to monitor vessel and fuel efficiency, which helps to record the key performance indicators such as main engine specific fuel oil consumption and total efficiency. Lloyd's register provides eco-assistant software to monitor the fuel consumption of main and auxiliary engines [17]. The monitoring, reporting, and analysis system of Kyma offers an overall ship performance evaluation. It is reported that the system can measure impact of antifouling on ship's performance [18]. Selmacontrol developed a ship energy efficiency monitoring system (SEEMS) to monitor main engine and hull conditions. Wang et al. designed a ship energy efficiency monitoring and control system to calculate the EEOI and optimize propulsion efficiency [19]. Their system is mainly installed on

passenger ships sailing on the Yangtze River. Perera et al. monitored the ship's average draft, weather conditions, and main engine performance to identify the best trim configurations [20]. KROHNE EcoMATE can accurately record fuel consumption. The energy management (EM) system from Rolls Royce offers decision-making approach to reduce fuel consumption and operating costs [21]. Based on the collected data, Capezza et al. [22] used statistical methods to analyze abnormality and used the partial least square algorithm to do fuel consumption regression. The aforementioned systems can assist in decision support and assess ship performance trends. However, their systems usually do not provide online real-time monitoring and evaluation for company management on land. Real-time monitoring of some key performance indexes is of great importance to evaluate the ship state and improve its efficiency.

Deng et al. [23] analyzed and predicted ship energy efficiency based on 6G communication technology. Although they can access the data in real time, their research focuses on the inland river ships and the ocean-going ships lack the corresponding communication conditions. Their energy efficiency assessment is based only on the specific fuel consumption rate per shaft power of the main engine. Erol et al. [24] evaluated the impact of fouling on ship energy efficiency through correlation analysis between ship speed and main engine power. The curve fitting method is applied to fit the data, but data preprocessing is lacking, which leads to some confusion in the visualization of data points. This paper also analyzes the correlation between ship speed and main engine power to find out the impact of ship body fouling but averages the data on the same abscissa before visualization and evaluation. In order to finish the propulsion power measurement, Bonisawski et al. [25] proposed a novel telemetry system and achieved real-time measurement. It focuses on the data measurement and collection. Vorkapi et al. [26] compared the linear regression, multilayer perceptron, support vector machine, and random forest. They suggest that the random forest can predict with high accuracy. However, they require more analytical comparison. Adland et al. [27] evaluated the impact of hull fouling on fuel consumption through regression analysis of daily fuel consumption and ship speed. However, not only due to fouling of the hull but also due to the reduced performance of the diesel engine, the fuel consumption of the ship after being put into use has also increased. They did not rule out the influence of factors such as changes in diesel engine operating conditions.

In order to increase shore-based support capabilities, an online transmission and monitoring system for energy efficiency data based on the BeiDou System was designed and developed in this paper. Unlike other systems, the system installed on the ocean-going ships can send monitored data to the shore in real time. The system collects a big amount of data and stores the data in the database. Big data and physics-based methods are applied to analyze data and provide intelligent decision making. The system is featured as follows.

(1) While many previous systems are working offline, in this work, ship energy efficiency-related data are transmitted to the shore data center in real time. It is easy to find out any operations or technologies that can save fuel by the designed system, and it is easy to find out any abnormal fuel consumptions by analyzing the historical data. Any operational changes will be notified to company management in time.

(2) Principal component analysis (PCA) algorithm is applied to reduce the features' dimension, and it is found that the shaft power is the main component.

(3) In addition, through the performance evaluation by collected big data, the system can support decision making to determine whether the ship is in a fouled state and choose an optimal ship trim to reduce fuel consumption.

The main contributions of this paper can be summarized as follows. Many studies applied a single method, using only one of the machine learning and physics-based analyses. However, the two methods are combined in this paper. Although PCA has been used in ship energy efficiency analysis, it is used to express the importance of different input features. This paper applies it to better visualize the data, makes a good fuel consumption correlation chart, and finds the principal elements in the data. Novel physics-based methods help determine the condition of the ship and select the best trim. The fouling greatly affects the ship's resistance, which makes the ship speed reduce about 11.37% in one year. At the same time, it was discovered that for specific loading conditions, there is an optimal ship trim that can reduce fuel consumption.

The rest of this paper is arranged as follows. In Section 2, the problem and objectives of this research are provided. Section 3 presents the PCA and curve fitting methods. The big data system for ship energy efficiency monitoring is presented in Section 4. Section 5 presents the data overview and visualization. The physics-based analysis of the energy efficiency is introduced in Section 6. At last, conclusions are made in Section 7.

2. Problem and Objective Description

A ship sailing on the vast ocean consumes a lot of fuel. In order to monitor the condition of the ship body and main engine in time, it is necessary to establish a monitoring system. The system should record influencing factors of fuel consumption, including meteorological conditions, load conditions, and power output. There is a need to solve the method of sending multidimensional variables to the shore in real time. After collecting big data, it is necessary to analyze the relationship between main engine power, main engine fuel consumption, rotational speed, and ship speed. How to exploit data and guide the establishment of measures to save fuel and reduce greenhouse gas emissions is still open to us and should be thoroughly studied. Many studies have completed the energy efficiency analysis, but few studies have been applied to online monitoring of ships in the actual marine environment. This paper narrows the gap between

research and actual use. A low-cost, high-reliability system is established for real-time measurement and monitoring of ship's load condition, fuel consumption, environmental changes, and other data. The method combining the machine learning and physics-based analysis is proposed to do further analysis on the data, which can assist in establishing fuel-saving measures.

3. Method Description

The principal component analysis is applied to the data visualization and determine the main component. For physics-based analysis, regression models are used to fit the data and determine the relationship between the data.

3.1. Principal Component Analysis. Dimensionality reduction helps to visualize the data. Projection and manifold learning are two main dimensionality reduction methods. The main axis can be found by projection. Principal component analysis (PCA) is a popular dimensionality reduction algorithm, which reduces the dimension by projection. The main idea of PCA is to map n-dimensional features to k dimensions. These k-dimensional features are brand new orthogonal features called principal components. PCA is to find a set of mutually orthogonal coordinate axes from the original space sequentially. The new coordinate axis is firstly chosen from the direction with the largest variance in the original data. By analogy, k coordinate axes can be obtained. In this paper, the PCA algorithm is based on singular value decomposition (SVD).

$$A = U \sum V^T, \tag{1}$$

where the original data A refer to an $m * n$ matrix with m samples and n features, U is an m-order square matrix (it contains orthogonal vectors which are called the left singular vectors), $\sum$ is a diagonal matrix, and V^T is the transposed matrix of V, which is an $n * n$ matrix, and its orthogonal vector is called the right singular value vector. PCA assumes that the dataset is centered at the origin, so the value of each feature needs to be subtracted from their average value first. That is, to first normalize each feature to zero mean and then apply SVD to find the principal components.

3.2. Regression Models. Both linear and polynomial regression models are applied to fit the data to show the relationship between variables.

3.2.1. Linear Regression Model. Linear regression model adds up input features with different weight and intercept terms, as in (2). After determining the weight and intercept terms, it can be used to predict the target variable.

$$\widehat{y} = \theta_0 + \theta_1 x_1 + \cdots + \theta_i x_i + \cdots + \theta_n x_n = \boldsymbol{\theta}^T \cdot \mathbf{x}, \tag{2}$$

where n is the dimension of the features, x is the input vector, and θ is the vector containing the weight and intercept terms. To determine the weight and intercept terms, both the standard equation based on the least square method

and the gradient descent method can be used. The standard equation (3) can minimize the MSE cost function as in (4).

$$\boldsymbol{\theta} = \left(\mathbf{x}^T \cdot \mathbf{x}\right)^{-1} \cdot \mathbf{x}^T \cdot y, \tag{3}$$

$$J(\theta) = \mathrm{MSE}(\theta) = \frac{1}{m}\sum_{i=1}^{m}\left(\widehat{y}_i - y_i\right)^2. \tag{4}$$

3.2.2. Polynomial Regression Model. The linear model is simple, but it can only show linear correlation. Polynomial regression can fit nonlinear data. It is also easy to add the polynomial terms to the linear regression model to complete the polynomial regression.

In regression, the coefficient of determination (R^2) as in (5) is used to show the applicability of the model. The value range of the coefficient of determination (R^2) is between 0 and 1.

$$R^2(y, \widehat{y}) = 1 - \frac{\sum_{i=1}^{m}\left(y_i - \widehat{y}_i\right)^2}{\sum_{i=1}^{m}\left(y_i - \overline{y}\right)^2}, \tag{5}$$

where $\hat{y}_i$ is the regression value of the model, y_i is the target value, and m is the number of data.

4. Big Data System for Ship Energy Efficiency Monitoring

If fuel consumption and its influencing factors are not measured, it is difficult to reduce fuel consumption. A big data collection system has been developed. The system is used for the monitoring, collection, reporting, and analysis of ship energy efficiency data and can send reliable real-time data to the data center onshore. It is user friendly and customizable. The system fully complies with the regulatory requirements for energy data collection, which is another main feature of the system.

Figure 1 shows the framework of the system. A data acquisition module (DAM) receives messages from sensors and other systems, then decodes the messages, and inserts data series into the database. Meanwhile, the ship energy monitoring systems obtain and send the data to the shore-based data center by BeiDou System (BDS). After it receives data, the server on the shore side will also store the data series in the database. Then, company managers can use mobile phones, computers, and laptops to retrieve real-time data.

Since data transmission is designed on the basis of BeiDou System to facilitate shore monitoring, real-time and integrated display of energy efficiency data can be achieved. The BeiDou System is characterized by low cost. It offers a free short message communication service through its satellites. The system is also reliable. It is one of the four global satellite navigation and positioning networks, alongside America's GPS, Russia's GLONASS, and Europe's Galileo system [28]. The 55th BeiDou Satellite III was launched on June 23rd 2020 and has been tested and put into full use. The BeiDou network already has more than 99% coverage globally.

As shown in Figure 1, the system collects data from flow meters, onboard Global Positioning System (GPS) receiving device, anemometer, Doppler speed log, shaft power monitor, etc. In addition, the system can communicate with liquid level system (LLS), engine room alarm, and monitoring system (AMS).

The flow meters used in our system are mass flow meters, which are more accurate than volume flow meters. The measurement of fuel consumption is highly accurate. They communicate with DAM via controller area network (CAN) provided by an add-on module. Other sensors are the devices already used on board. They send out data according to the IEC 61162-1 standard. The messages are coded with National Marine Electronics Association (NMEA) protocol. However, they are usually installed on bridge. RS-485 is applied to transfer data from bridge to engine room. LLS and engine room AMS are connected to DAM by Ethernet. The draft of ship is obtained from LLS, and the power of diesel generator is read from AMS.

Table 1 shows the data obtained from the sensors. The flow meters are installed at the inlet and outlet of the fuel oil pipes of main engine, diesel generators, and boiler. The real-time fuel oil consumption of main engine, diesel generators, and boiler can be fetched by the flow meters. The main engine is a device that consumes most of the fuel, and its fuel consumption is affected by many factors, including weather and load conditions, engine performance, and ship fouling. The load and weather conditions are recorded to evaluate the engine efficiency.

The temperature and density of fuel oil are also recorded. From the Doppler speed log and GPS, the water referenced and ground referenced ship speed and ship location are fetched and recorded. Other monitoring values include relative wind speed and direction, diesel generator power, ship draft on the front, rear, port, and starboard sides, shaft speed, torque, and power. In addition, the rudder angle can be obtained from the rudder angle indicator if the ship owner needs it. Ship's heading and water depth may also be connected to our system.

The system is fully customizable. All the values are fetched and stored in the database. The unit and remark of some fields in the database are shown in Table 2. It should be noted that the slip ratio of propeller (ShipSlip), ME specific fuel oil consumption per kilowatt of shaft power (MESFOC_kw), and ME fuel oil consumption per knot of ship speed (MESFOC_nmile) are calculated and stored too, which are very important for the monitoring of main engine.

Since data can be obtained in real-time onshore, it can help to find fuel-saving operations and technologies. Managers can also analyze data to find abnormal fuel consumption and avoid improper operation of equipment that may cause high fuel consumption.

5. Data Overview and Visualization

The system has been installed on two sister container ships of SITC International Holdings and has been operating reliably for more than a year. Two more sister ships will also install the same system, which is delayed by the epidemic.
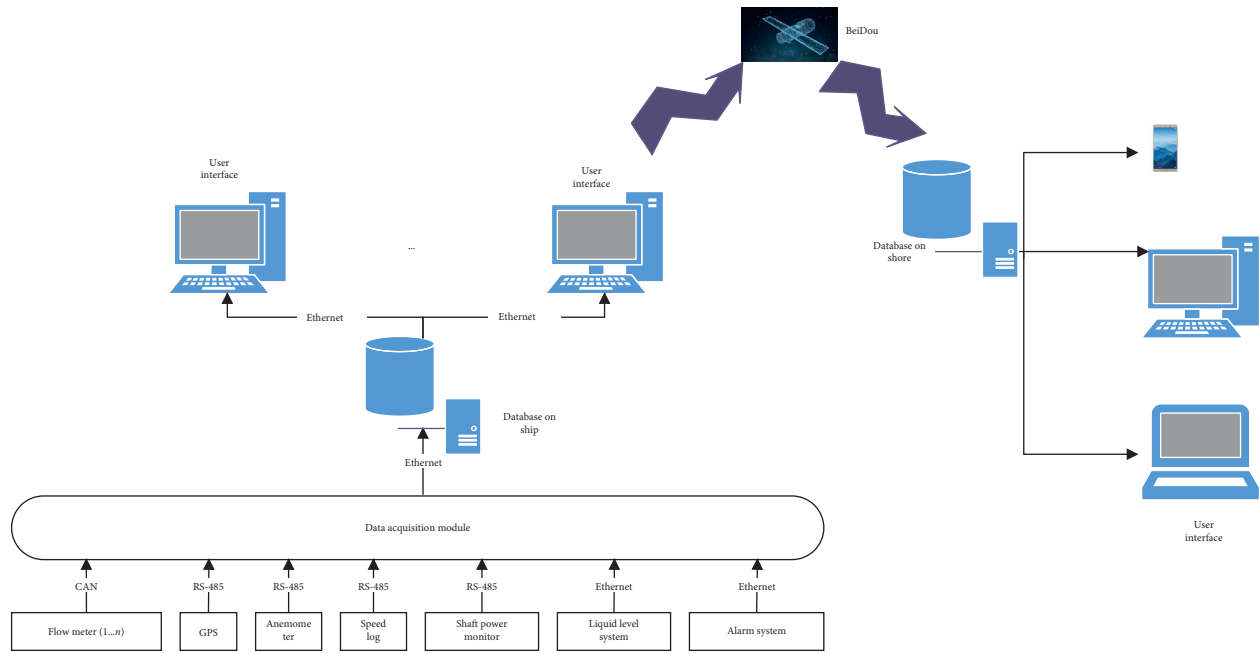
FIGURE 1: Ship energy efficiency monitoring system.

TABLE 1: Data acquisition from sensors.

Sensor	Data
Flow meters	Fuel oil consumption
Anemometer	Relative wind speed and direction
Doppler speed log	Water referenced ship speed
GPS receiving device	Ship position, ground referenced ship speed
Alarm system	DG power
Liquid level system	Ship draft
Shaft power monitor	Shaft speed, torque, and power

TABLE 2: Unit and remark of fields.

Field name	Unit	Remark
PCDate	YYYY-MM-DD	Record date
PCTime	hh:mm:ss	Record time
MEActFOCons	kg/h	ME fuel oil consumption rate
DGActFOCons	kg/h	DGs fuel oil consumption rate
BlrActFOCons	kg/h	Boiler fuel oil consumption rate
DG1Power	kW	Power of no.1 DG
DG2Power	kW	Power of no.2 DG
DG3Power	kW	Power of no.3 DG
MERPM	r/min	ME shaft revolution speed
METorque	kN∗m	ME shaft torque
MEShaftPow	kW	ME shaft power
ShipSpdToWater	Knot	Water referenced speed
ShipSpd	Knot	Ground referenced speed
ShipHeel	m	Draft port-draft starboard
ShipTrim	m	Draft rear-draft front
ShipDraft	m	(Draft rear + draft front)/2
WindSpd	Knot	Relative wind speed
WindDir	°	Relative wind direction
Latitude	°, ', " (N/S)	Latitude
Longitude	°, ', " (E/W)	Longitude
ShipSlip	%	Slip ratio of propeller
MESFOC_kw	g/kW∗h	ME fuel consumption/kW (power)
MESFOC_nmile	kg/nautical mile	ME fuel consumption/knot (speed)

The two ships are named as SITC BATANGAS and SITC CEBU. The system records data every 10 seconds. Many data series have been stored. These container ships have been sailing on the same route and can carry 2,400 twenty equivalent units (TEUs). Their length is 189 meters and width is 32 meters. They are equipped with the same main engine (ME), diesel generators (DGs), and boiler. The ships consist of a main engine (MAN B&W 7S60ME-C10.5) (two-stroke diesel engine with maximum continuous rating 13,700 kW ∗ 97 r/min), three diesel generators, an exhaust gas boiler, and an oil-fired boiler. The main engine drives the fixed pitch propeller directly. Their propeller has 4 blades and an average pitch of 6,134 millimeters.

5.1. Data Overview. The system has been put into use since October 2019. In 2020, more than 1.5 million valid data have been recorded. When the ship is in port, the energy efficiency-related data are meaningless, so the data in this area are deleted. The water referenced speed of SITC BATANGAS remained unchanged at 9.6 knots for about six days, which may have been caused by abnormal sensor communication, and these records are also deleted. Part of the

data is in the accelerating and decelerating state of the main engine, where MESFOC_kw, MESFOC_nmile, or ShipSlip is far away from normal value, and these data will not be used in the analysis too. The area below 15 r/min (RPM) is not the long-running area of the main engine, which is also deleted. At last, SITC BATANGAS has a total of 1,485,708 records,

while SITC CEBU has a total of 1,506,452 records in 2020. In Sections 5.1 and 5.2, the data overview and visualization of SITC CEBU are taken as a case study.

Figure 2 shows the histogram plots of main engine energy efficiency-related variables, which can show their distributions. In the figure, the horizontal axis is the variable area, and the vertical axis is the count of the variable. The figure shows that all the variables are within a reasonable range.

5.2. Data Visualization.

5.2. Data Visualization. Figure 3 shows the correlation between the ship's water referenced speed and shaft power. It can be found that the main engine power and the ship's water referenced speed are concentrated in three regions, with speeds of about 10, 13, and 16 knots as the center. The ship speed is mainly determined by the engine power. The main engine is mainly operated in the three centers of shaft power, and the entire engine-related variables change accordingly.

Some researchers applied PCA in the feature importance analysis; however, they used it to analyze the parameter relationships. The PCA method is applied to discover two main features in this paper. PCA can find which feature contributes most to the difference. The PCA method operates to reduce energy efficiency data to two dimensions and proves that the shaft power and wind direction are the two main features. In addition, the shaft power contributes 99.575% of the variance, while the wind direction contributes 0.396%. The remaining features only account for only 0.029% of the variance. The main component must be the shaft power, which relates to the load of main engine. However, the load of the main engine is closely related to the ship's speed, load distribution, and weather conditions of the ship. They influence each other and have a close relationship. Figure 4 shows the plot after the dimension of features is reduced to three. The semitransparent plane is the projection plane of the data. When engine power increases, the fuel consumption per knot of ship's speed (MESFOC_nmile) increases linearly on the projection plane. The blue points are the points with MESFOC_nmile higher than the value on the projection plane, and the black points are those less than the projection plane.

Figure 5 shows the correlation between the ship's draught and trim, and the ship's trim is negatively correlated with the draught. When the ship is in ballast, its draft is only 6 meters and its trim is close to 4 meters. After the ship is full loaded and its draft is higher than 10 meters, the ship officers adjust the ship to the horizontal state and its trim is close to zero.

6. Results of Energy Efficiency Analysis

As it is known to us, ship's speed, main engine shaft power, and its fuel oil consumption are interrelated with each other. However, for every ship engineer, even the person in charge of shipping company, the exact mathematical model under actual navigation factors may not be very clear. Since a large amount of data from two vessels is collected in more than one year, data analysis is completed in order to retrieve their relationship, which may facilitate the evaluation of ship

performance. A physics-based analysis software is designed based on C# language, which can help to make decisions to reduce the fuel consumption. The relationship between the features is analyzed first. The analysis will also introduce some measures to improve energy efficiency.

6.1. Relationship of Shaft Power and Shaft Speed under Different Load Conditions.

6.1. Relationship of Shaft Power and Shaft Speed under Different Load Conditions. First, the relationship of the shaft power and shaft speed under ballast and laden conditions is compared as shown in Figure 6. In Figure 6, the data value is taken as the logarithm to the base 10. Linear regression is applied to fit the data. The relationship between shaft power and revolution speed is close to power of 2.5 to 2.6. The result shows that there is no clear difference between two conditions. The main difference lies in the low load area, where the ship has a higher resistance under full load and requires more power. The points are overlapped and the trend lines are nearly the same under the ship's two different loading conditions.

6.2. Relationship of Shaft Power and Ship's Speed under Different Slip Ratios.

6.2. Relationship of Shaft Power and Ship's Speed under Different Slip Ratios. The relationship between shaft power and ship speed is closely related to the slip ratios (ShipSlip). As shown in Figure 7, the trend lines of ME Shaft Power-Ship Speed under different slip ratios are clearly separated with each other. The power required for a certain ship speed will increase as the slip ratio increases. The fouling of the ship hull and propeller will cause an increase in slip ratios, so attention must be paid. In addition, weather routing is also of great importance that it can avoid the bad weather conditions.

Through the analysis software, the relationship between shaft power and water referenced ship speed in different periods can be obtained. Therefore, the newly acquired data can be compared with the data collected when the ship was just launched to help determine whether the ship is in a fouling state. Figure 8 shows the relationship between shaft power and ship's speed in two different periods. These two time periods are January 2020 and January 2021, respectively. The points where the ship is in full load and the ship's speed is above 11 knots are selected. The points in 2021 are much higher than those in 2020 in Figure 8, which means more engine power is needed for the same ship's speed. In Jan. 2020, the average shaft power of the ship was 4,464.03 kW and the average speed was 14.63 knots. In Jan. 2021, the average shaft power was 4649.86 kW, but the average speed was only 12.96 knots. For the same engine power output, fouling reduced the ship's speed by approximately 11.37% within one year.

Adland et al. [27] determined the impact of hull fouling through the regression of ME fuel consumption rate. As shown in Figure 9, the fuel consumption in Jan. 2020 is higher than that in Jan. 2021. However, it cannot rule out the performance degradation of main engine. Figure 10 shows that the fuel consumption per kilowatt of shaft power is a little higher in Jan. 2021 than Jan. 2020. In our work, the fouling impact is studied by the change of shaft power, which
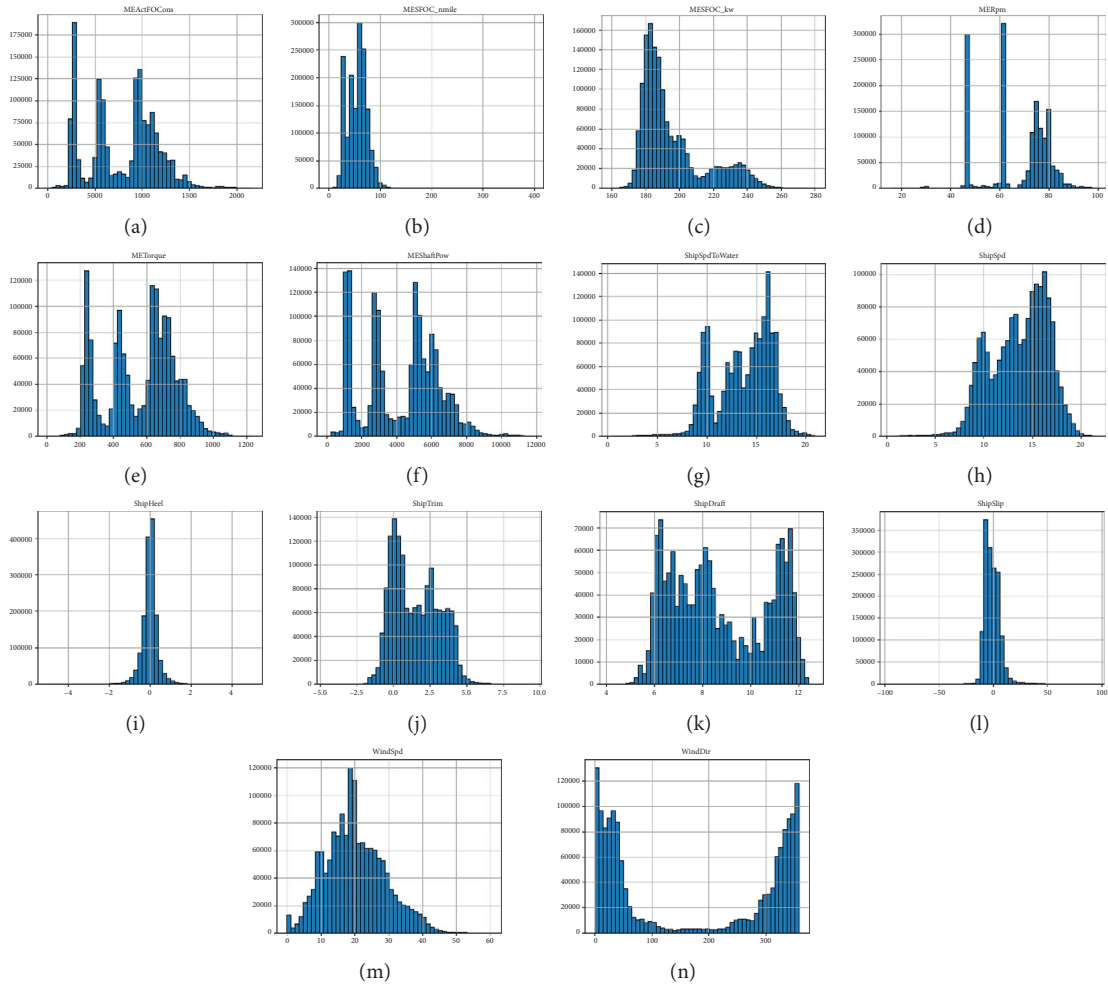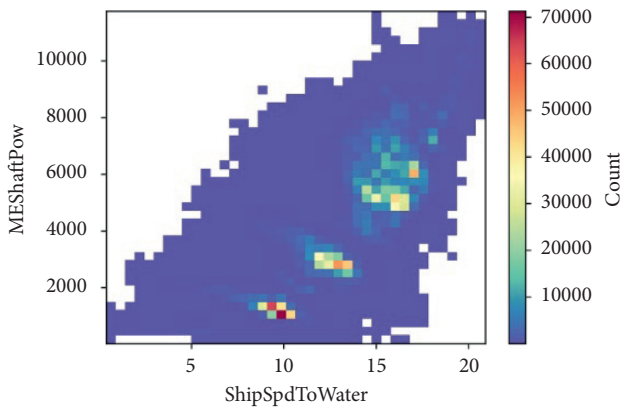
FIGURE 2: Histogram plots of variables.

FIGURE 3: Correlation between ShipSpdToWater and MEShaftPow.

FIGURE 4: Plot of features reduced to three dimensions.

is directly related to the ship's resistance. The ship's resistance is increased when the hull is fouled.

6.3. Relationship of Main Engine Fuel Consumption per Nautical Mile and Ship's Speed.

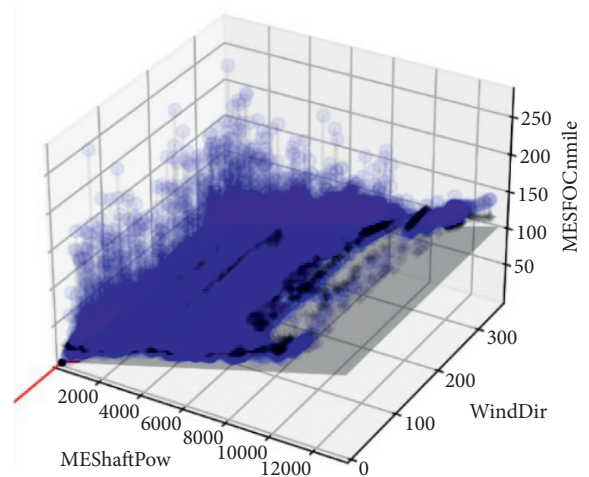The fuel consumption per nautical mile (MESFOC_nmile) of the main engine is related to its combustion status, the resistance of the ship, and some other factors. It mainly depends on the maintenance of the engine and the load of the engine, as well as the propeller propulsion efficiency. Ship speed is mainly determined by the engine power and ship resistance. The relationship
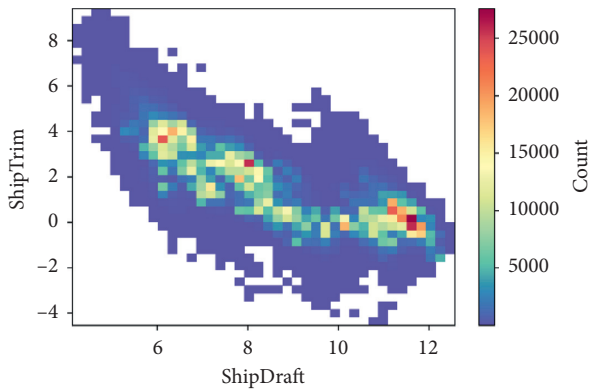
Figure 5: Correlation between ship's draught and trim.

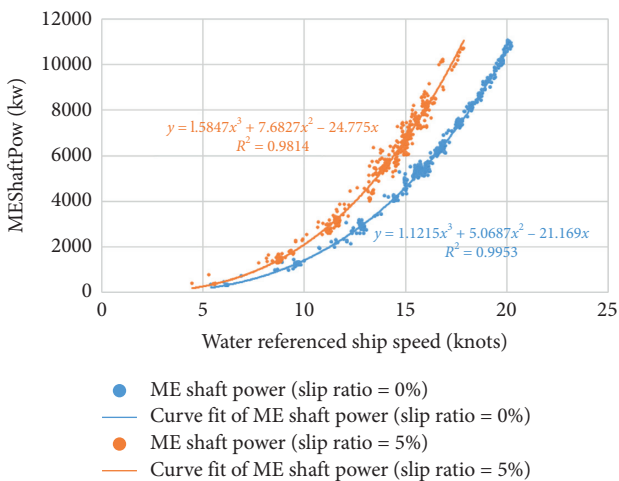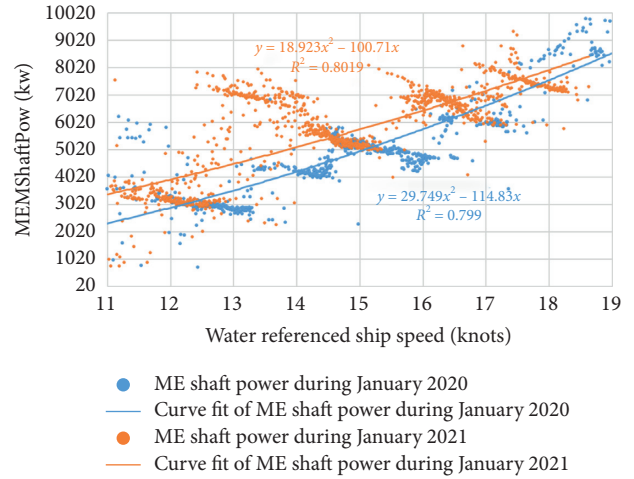Figure 8: Relationship of shaft power and ship's speed in two different periods.

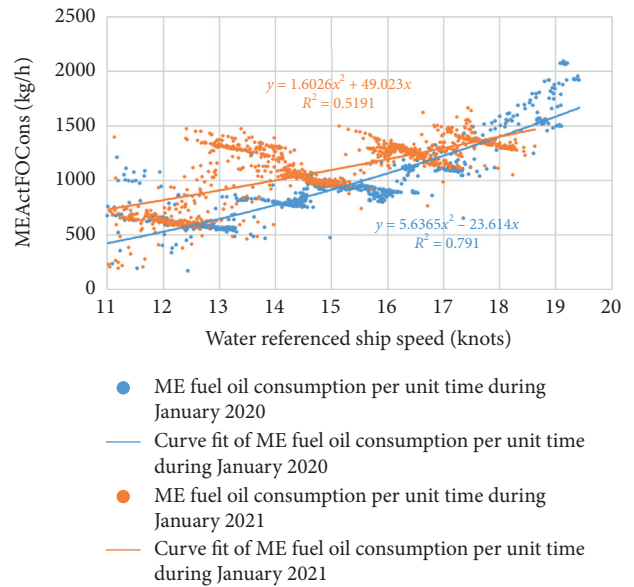Figure 6: Relationship of shaft power and shaft speed under ballast and laden conditions.

Figure 9: Relationship of ME fuel consumption rate and ship's speed in two different periods.

between fuel consumption per nautical mile and ship speed will be compared between the two sister ships.

The combination of MESFOC_nmile and ship's speeds is selected with the same slip ratio. The main engine fuel consumption per nautical mile of SITC BATANGAS is a little less than that of the SITC CEBU under the same ship speed as shown in Figure 11. It is necessary to make a detailed comparison of the operating conditions of the main engines on the two ships to find out the exact reasons. The better fuel efficiency per ship's speed of SITC BATANGAS may be related to the operating status of the main engine. It is worth collecting more engine operating parameters (exhaust temperature, intake air temperature, cooling water temperature, lubricating oil temperature, etc.) for in-depth research.

Figure 7: Relationship of shaft power and ship's speed under different slip ratios.
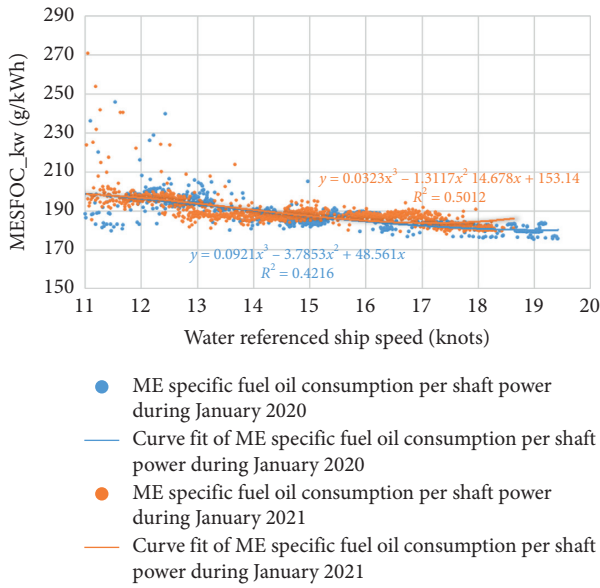
FIGURE 10: Relationship of ME specific fuel oil consumption and ship's speed in two different periods.
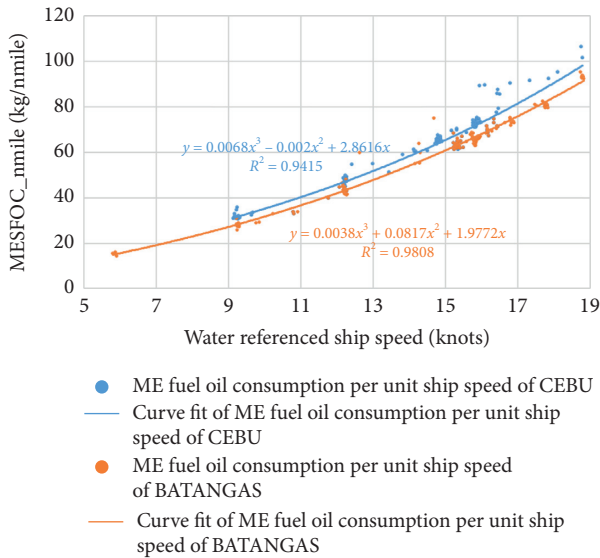

FIGURE 11: Relationship between MESFOC_nmile and ShipSpd of two sister ships.

6.4. Optimal Ship Trim Selection. The fuel consumption rate per nautical mile (MESFOC_nmile) of main engine is related to the ship trim. The collected data can be used to find the best ship trim to reduce fuel consumption. Under the same ship draft and ship speed, we filter the MESFOC_nmile with different ship trims. As shown in Figure 12, the MES-FOC_nmile is the smallest when the ship trim is close to zero under full load. However, in the ballast state, the ship trims are all higher than 0, and the best trim from the data is about 3.6 meters, as shown in Figure 12. Note that the ship trim here is equal to "stern draft-bow draft."

Therefore, the analysis of the data can help to choose an optimal ship trim under different load conditions and ship
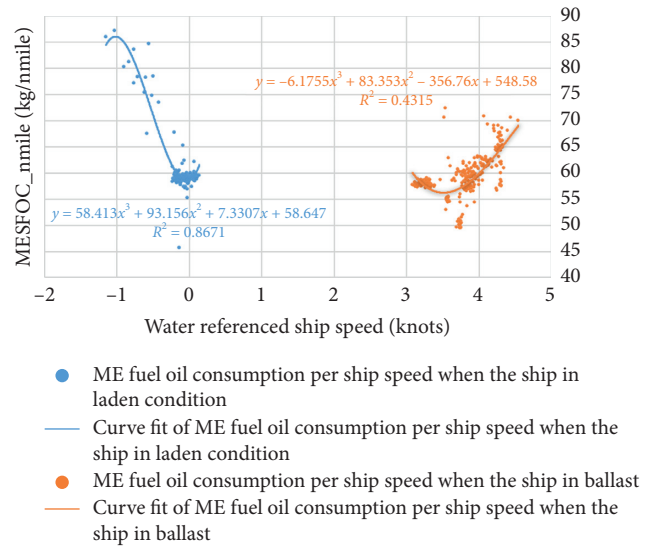

FIGURE 12: MESFOC_nmile-trim curve of SITC CEBU.

speeds. When fully loaded, the horizontal state can make the resistance of the ship smaller than other states. In fact, the ship has been optimized in the fully loaded horizontal state. However, fuel savings would be considerable when the ship is in ballast. In ballast, proper ship trim will reduce the ship's resistance, thereby reducing fuel consumption.

7. Conclusion

In this paper, the relationship between multidimensional data is analyzed first. Through the PCA, it is established that the shaft power is the main component of the data. The correlation analysis between the parameters is completed through the statistics of the number of data. Then, based on the physics-based method, it is determined that the ship's loading condition has little effect on the power, and the slip ratio of the propeller has a strong influence on the power consumption. Moreover, after the one-year voyage, the fouling of the ship has caused an increase in hull resistance, and attention should be paid at all times. The difference in draft also greatly affects fuel consumption; especially in ballast situations, the optimal draft should be paid attention to. In conclusion, the following phenomena are noticed.

(1) When the ship is under different load conditions, there is no significant difference in the ME Shaft Power-Shaft Speed trend curve.

(2) The ME Shaft Power-Ship Speed has obvious different slopes under different slip ratios. The higher the slip ratio, the greater the power required for the same ship speed. Therefore, the slip ratio can be used as an indicator to show the navigation conditions. The changing trend of the ME Shaft Power-Ship Speed in two periods can help assess whether the ship hull is fouled.

(3) Under full load and ballast conditions, the best ship trim with minimum fuel consumption may be different. Analysis of the data can help to choose an optimal ship trim.

(4) After comparing the two sister ships from the collected data, the fuel saving performance of SITC BATANGAS is better because of its lower fuel consumption per ship speed. It is worth collecting more operating parameters to carry out an in-depth study. Our further study will carry out an in-depth study on the reason why the SITC BATANGAS has a better fuel-saving performance.

Data Availability

A large amount of data was collected from two sister container ships of SITC International Holdings. Since the data belong to the company, we cannot publish them completely. After obtaining the company's authorization, any requirements for some data can be met.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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