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Energy-efficient shipping

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Energy-efficient shipping: An application of big data analysis for optimizing engine speed of inland ships considering multiple environmental factors

Xinping Yan[a,b,c], Kai Wang[a,c,d,**], Yupeng Yuan[a,b,e,*], Xiaoli Jiang[d], Rudy R. Negenborn[d]

[a] Reliability Engineering Institute, School of Energy and Power Engineering, Wuhan University of Technology, Wuhan, 430063, China
[b] National Engineering Research Center for Water Transportation Safety (WTSC), MOST, Wuhan, 430063, China
[c] Key Laboratory of Marine Power Engineering & Technology, (MOT), Wuhan University of Technology, Wuhan, 430063, China
[d] Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Mekelweg 2, Delft, 2628, CD, the Netherlands
[e] Department of Engineering, University of Cambridge, Cambridge, CB3 0FA, UK

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ABSTRACT

Energy efficiency of inland ships is significantly influenced by navigational environment, including wind speed and direction as well as water depth and speed. The complexity of the inland navigational environment makes it rather difficult to determine the optimal speeds under different environmental conditions to achieve the best energy efficiency. Route division according to the characteristics of these environmental factors could provide a good solution for the optimization of ship engine speed under different navigational environments. In this paper, the distributed parallel k-means clustering algorithm is adopted to achieve an elaborate route division by analyzing the corresponding environmental factors based on a self-developed big data analytics platform. Subsequently, a ship energy efficiency optimization model considering multiple environmental factors is established through analyzing the energy transfer among hull, propeller and main engine. Then, decisions are made concerning the optimal engine speeds in different segments along the path. Finally, a case study on the Yangtze River is performed to validate the present optimization method. The results show that the proposed method can effectively reduce energy consumption and CO_2 emissions of ships.

1. Introduction

Waterway transportation is playing an irreplaceable role in the economic development (Hoffmann and UNCTAD, 2015). However, it also leads to an array of concerning issues, such as high energy consumption and environment pollution (Doulgeris et al., 2012; Wan et al., 2016; Walsh and Bows, 2012). Due to the rising fuel prices (García-Martos et al., 2013), shipping companies face great challenges to reduce operating costs and improve market competitiveness. Moreover, according to the green-house gas (GHG) study by the IMO (IMO, 2009), international shipping accounts for approximately 2.7% of the total CO_2 emitted globally. Inland ships also have these problems. Take Yangtze River as an example: the yearly ship emission of CO_2 reaches 5.27 million tons (Li, 2010). These emissions inevitably impose a negative impact on the cities along the waterway. For this reason, energy efficiency optimization and improvement of inland ships is an essential task for the development of environmentally friendly and efficient shipping methods.

To facilitate the energy efficiency optimization of a large set of ships in service, researchers have studied and proposed various measures on energy conservation and emission reduction, including new energy application (Burel et al., 2013; Attah and Bucknall, 2015; Vergara et al., 2012), navigation optimization (Norstad et al., 2011; Wang et al., 2018), and operation management and control strategies (Molina et al., 2014; Liu et al., 2013; Guan et al., 2014; Wang and Meng, 2012; Wang et al., 2015). Speed optimization, with the advantage of requiring no ship modification and lower investment, is strongly favored against other measures (Faber et al., 2010). In the previous studies, a series of speed optimization methods were investigated (Corbett et al., 2009; Lindstad et al., 2011; Psaraftis and Kontovas, 2013, 2014; Chang and Chang, 2013; Fagerholt et al., 2010; Magirou et al., 2015). These studies are roughly based on two approaches: 1) analyzing the influence of speed on the operational economics and CO_2 emissions so as to assess the overall improvement potential; 2) optimizing the routing and scheduling of ships based on sailing speed adjustment from the perspectives of maritime logistics and operational management. In general,

* Corresponding author. Reliability Engineering Institute, School of Energy and Power Engineering, Wuhan University of Technology, Wuhan, 430063, China.,
** Corresponding author. Reliability Engineering Institute, School of Energy and Power Engineering, Wuhan University of Technology, Wuhan, 430063, China.
E-mail addresses: wangkai1990@whut.edu.cn (K. Wang), yy440@cam.ac.uk, ypyuan@whut.edu.cn (Y. Yuan).

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these two types of speed optimization methods address the issue on a more macroscopic level, i.e., they focus exclusively on seagoing ships while optimizing the sailing speeds between different legs, assuming that the fuel consumption for a given sailing speed and weather condition is known and constant (fuel consumption is typically a cubic function of speed). By contrast, few studies focus on inland ships. In addition, for a given sailing speed, the fuel consumption can vary significantly due to the influence of weather conditions. To date, there are limited studies on the relationship among engine speed, fuel consumption and environmental factors, let alone the development of a decision-making method for optimizing engine speed considering the influence of various environmental factors.

Due to the strong interaction between propulsion system and navigational environment, the energy consumption of a ship's main engine is influenced significantly by complex environmental factors including water speed and depth as well as wind speed and direction (Zhao et al., 2016; Wang et al., 2016a). These factors can result in an increase of hydrodynamic resistance force, which consumes a large portion (28%) of the overall propulsive force eventually (Marine Environment Protection Committee, 2009). Lin et al. (2013) analyzed the influence of weather conditions on fuel consumption during sailing by using a three-dimensional modified isochrones method. Lee et al. (2018) revised the empirical function for predicting fuel consumption and sailing speed by considering the effect of wind and current on fuel consumption, and then proposed a speed optimization model from the perspective of maritime logistics. These studies either only focus on the speed optimization of seagoing ships while neglecting the influence of location-dependent weather conditions on ship's energy efficiency, or only consider several environmental factors. Besides the seagoing ships, one also needs to comprehensively consider the wave and wind as well as the water speed and depth due to their significant influence on the energy efficiency of inland ships (Sun et al., 2013; Zheng et al., 2016). The complex navigational environment of the inland waterway makes it very difficult to determine the segment-dependent optimal engine speeds along the entire route. A previous study carried out a sensitivity analysis concerning the influence of environmental factors on the energy efficiency of inland ships (Yan et al., 2015), which laid a solid foundation for determining optimal engine speeds under various weather conditions. The environmental factors in different segments exhibit different characteristics, leading to a variation of impacts on the ship energy efficiency. Hence, the optimal speed also varies from segment to segment, especially when the environmental factors are subject to marked variation along the entire route. As such, it is advised to divide the route into a set of small segments, based on which segment-dependent speed optimization of inland ships can be achieved by accounting for multiple regional environmental factors so as to maximize the overall energy efficiency. To our best knowledge, such decision-making method for determining segment-dependent optimal engine speeds has not yet been published before.

This paper aims to develop an engine speed optimization workflow based on big data analytics that takes multiple environmental factors into consideration. This method can enhance the energy conservation and emission reduction of inland ships to the extent possible. The technical merits of the present paper are threefold: a) a distributed parallel k-means statistical analysis is proposed to cluster environmental factors into multiple groups, allowing an elaborate route division; b) a model for optimizing ship energy efficiency is built by analyzing the energy transfer among hull, propeller and main engine while considering multiple environmental factors, i.e., wind speed and direction as well as water depth and speed; and c) an algorithm is established to determine optimal engine speeds based on the corresponding environmental factors of different segments along the entire route, which results in an improved ship energy efficiency.

The remainder of this paper is organized as follows: Section 2 illustrates the existing methods; Section 3 proposes a new route division strategy based on environmental data analysis, followed by an elaboration of the engine speed optimization model and the corresponding solving method; Section 4 presents a case study on Yangtze River to demonstrate the applicability of this optimization method; and Section 5 summarizes main conclusions and proposes future research directions.

2. Methods

2.1. Big data analytics and its state-of-the-art applications

In recent years, big data has rapidly become a hot topic in the domains of science and technology. Nature and Science magazines have published monographs illustrating the opportunities and challenges associated with big data (Lynch, 2008; Wren, 2014). Big data is typically characterized by high volume, variety and velocity, i.e., three Vs, making it difficult to analyze the data efficiently using the traditional methods with limited data processing and calculation power (Dean and Ghemawat, 2008). Big data analytics is capable of extracting a significant amount of hidden information and knowledge by analyzing sizable datasets in various types so as to assist in the information illustration and decision making (Xie et al., 2017). With the advantages of being more comprehensive and accurate in revealing insights as well as less dependent on models, big data analytics has gained wide attentions from academia and industry in many different fields (Diamantoulakis et al., 2015; Xin et al., 2015).

Nowadays, decision making during inland ship navigation mainly relies on personal experience. Due to the lack of theoretical guidance, such approach is highly subjective, resulting in excessive energy consumption and serious environmental pollution. Therefore, there is a need to conduct ship navigation optimization based on scientific and well-informed decision-making derived from fundamental knowledge and representative data, including ship performance and navigation information. The application of big data analytics provides a new approach for ship manager and operators to boost the ship's energy efficiency, which echoes the modern trend of big data era. Over the last few years, extensive research efforts have been dedicated to the study of big data analytics and the development of platforms, resulting in significant achievements (Kambatla et al., 2014). Meanwhile, the application scope of big data analytics is becoming increasingly wide. In the maritime industry, the marine data has been leveraged to allow tsunami warning, disaster inversion, and visual modeling of hazards (Huang et al., 2015). Rødseth et al. (2016) analyzed the challenges and opportunities for applying the big data technology in shipping, and proposed that the big data analysis can be used for providing on-line decision support to ships, ship performance analysis, and fleet optimization. In addition, Perera and Mo (2016) focused on the ship energy efficiency optimization by using machine learning algorithms, including the pre-processing and post-processing of data. The rapid development of Internet of Things and communication technology promotes an explosive growth of data in the waterway transport, including environmental and operational information. The availability of information and the associated big data analytics can benefit from advanced information extraction and supreme computation efficiency, making it highly feasible to develop an effective speed optimization method under different environmental conditions so as to improve ship energy efficiency and reduce CO_2 emissions.

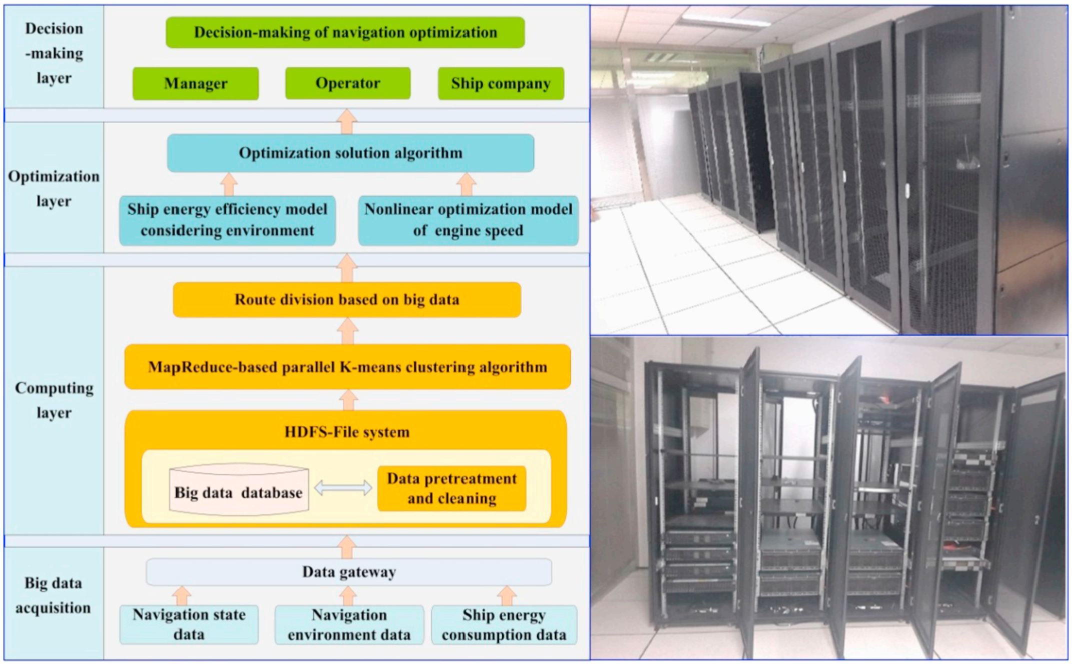


Fig. 1. Structure of the big data analysis platform.

2.2. *Big data analysis platform for ship navigation*

Compared with traditional data, the big data is characterized by its large scale, fast evolution, and high diversity, making it rather hard to analyze. Therefore, a rational design of big data platform is the basis for fully unlocking the potential value of big data in ship navigation optimization. To achieve this purpose, a big data analysis platform based on the widely used Hadoop framework is designed. The platform mainly consists of four functional layers, namely data acquisition layer, computing layer, optimization layer, and decision-making layer, as illustrated in Fig. 1.

The data acquisition layer is responsible for collecting data concerning the states of navigation, environment, and energy consumption. The collected data is then preprocessed and stored in the database system within the computing layer, which utilizes MapReduce-based algorithm and HDFS-based file system to realize data analysis for route division in this paper. Afterwards, in the optimization layer, the optimal solutions can be obtained based on an optimization model and the associated solver. Finally, the obtained optimization results are provided to the managers, ship owners and operators to drive the decisions concerning navigation optimization in the decision-making layer.

The MapReduce algorithm here is favored for its cost-efficient, scalable and easy-to-use natures, making it suitable for mining data on ship navigation optimization. The platform can make a full use of the distributed computing resources and achieve optimal allocation of these resources so as to significantly improve computational efficiency.

2.3. *Energy efficiency optimization method based on big data analysis*

The main purpose of energy efficiency optimization in this paper is to determine the optimal engine speeds in response to the segment-dependent environments along the entire route. The specific process of speed optimization is shown in Fig. 2.

Based on the obtained environmental information of the waterway,

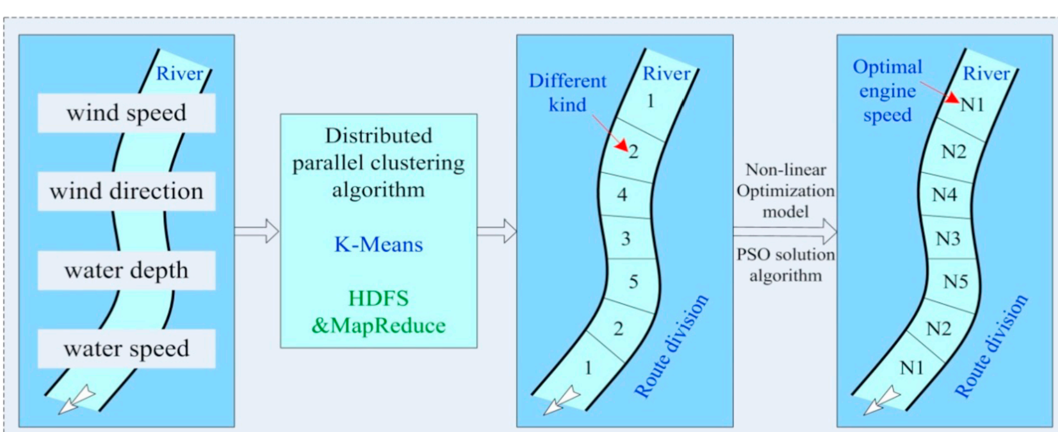


Fig. 2. Illustration of the speed optimization process.

the distributed parallel k-means algorithm is used to achieve the route division according to the various environmental factors. Based on this, the optimal engine speeds in different divisions can be obtained by establishing a non-linear optimization model concerning ship energy efficiency, which is in turn solved by the Particle Swarm Optimization (PSO) algorithm for reducing energy consumption and CO_2 emissions. The route division based on environmental data analysis and the engine speed optimization model considering multiple environmental factors are crucial to the optimization of ship energy efficiency, and are thereby detailed in the following sections.

3. Optimization of ship energy efficiency based on big data analysis

3.1. Route division based on the distributed parallel k-means clustering algorithm

The route division according to navigational environmental factors serves as the basis for engine speed optimization. k-means clustering algorithm is a type of clustering analysis based on the similarity theory. Compared with other clustering algorithms, e.g., canopy algorithm, the advantages of k-means clustering algorithm are three-fold: firstly, it is faster and simpler; secondly, it delivers higher efficiency and better scalability when it comes to processing large datasets; thirdly, it exhibits a linear time complexity, making it very suitable for mining large-scale datasets (Mehendale and Dhamal, 2016). Therefore, we propose to use the k-means clustering algorithm for the route division in this paper.

However, the need for handling a massive environmental dataset here makes the traditional clustering method impractical to use, and therefore the distributed parallel clustering algorithm based on the MapReduce becomes an ideal choice for making the runtime manageable. The implementation of the distributed parallel k-means clustering algorithm based on MapReduce is shown in Algorithm 1.

Algorithm 1. Distributed parallel k-means clustering algorithm.

```
1. Construct a main function to read the centroid file and get the center points
2. Use the map method in the mapper class to read the sample
3. For i = 0: center.length do
     Dis = CalculateDist(c_i, center[i]);
     if dis < Min_Dis {
       Min_Dis = dis;
       Keys = i;}
     end if
   end for
4. Output <Keys, Values> pair to the combine class.
5. The combine class calculates the sum of the samples in the same cluster and the
   sample number using a counter.
6. Output combined <Keys', Values'> pair to the reducer class.
7. Reducer class obtains the results from the map method to recalculate the centroid, and
   update the center points accordingly; the new results are written into the centroid file.
8. The driver class continually submits MapReduce job,
   if   Difference(new_center, old_center) < σ_min
        {terminate the iteration;
        report the final <Keys', Values'> pair}
   else
        {old_center = new_center;
        go to the next iteration;}
   end if
```

The route division according to multiple environmental factors can be achieved by running the distributed parallel k-means clustering algorithm on the newly developed big data analysis platform.

3.2. Engine speed optimization model based on the route division

3.2.1. Energy efficiency model considering multiple environmental factors

When a ship sails at a certain speed, the main engine should output enough power to overcome the hydrodynamic resistance forces, including hydrostatic resistance, wave-induced resistance, wind resistance, and shallow water resistance. The total resistance force can be calculated by using the published methods (Holtrop and Mennen, 1982; Kwon, 2008; Townsin et al., 1975; Hu, 1986) as shown in Eqs. (1)–(6), where the total resistance force is expressed as a function of sailing speed, wind speed, wind direction, water speed, and water depth etc.

$$R_T = R_F(1 + k_1) + R_{APP} + R_W + R_B + R_{TR} + R_A \tag{1}$$

$$R_{\text{wave}} = \frac{1}{2}\frac{0.065}{(F_r)^2}\left(\frac{h}{L_{\text{wl}}}\right)^2 \rho S V_S^2 \tag{2}$$

$$R_{wind} = \frac{1}{2} C_{wind} \rho_{air} A_T V_{wind}^2 \tag{3}$$

$$R_{shallow} = f_s \cdot R_{deep} \tag{4}$$

$$f_s = 1 + \frac{0.065V_S^2}{(\frac{H}{d} - 1)\sqrt{d}} \tag{5}$$

$$R = R_T + R_{wave} + R_{wind} + R_{shallow} \tag{6}$$

where, R_T denotes the total hydrostatic resistance; R_F denotes the frictional resistance; R_{APP} denotes the appendage resistance; R_W denotes the breaking waves resistance; R_B denotes the additional resistance of the bulbous bow; R_{TR} denotes the stern leaching additional resistance; R_A denotes the related resistance of the model ship; k_1 denotes the ship viscous resistance factor; F_r denotes the Froude number; h denotes the wave height; L_{wl} denotes the waterline length of the ship; ρ denotes the density of water; S denotes the wet area of the ship; V_s denotes the ship's hydrostatic speed; R_{wind} denotes the wind resistance; C_{wind} denotes the coefficient of wind resistance; ρ_{air} denotes the air density; A_T denotes the windward area; V_{wind} denotes the relative wind speed; $R_{shallow}$ represents the shallow water resistance; R_{deep} indicates the deep water resistance; f_s is a conversion coefficient; H represents the water depth; d denotes the ship's draft; R denotes the total resistance of the ship.

For a given engine speed, the thrust and torque of the propeller can be expressed using the following equations:

$$T = K_T \times \rho n^2 D^4 \tag{7}$$

$$Q = K_Q \times \rho n^2 D^5 \tag{8}$$

where, K_T is the thrust coefficient of the propeller; K_Q is the torque coefficient; ρ is water density; n is the propeller speed; D is diameter of the propeller; K_T and K_Q can be obtained using the interpolation polynomials method (Bernitsas et al., 1981):

$$K_{T,Q} = f_{T,Q}(J) \tag{9}$$

where, J denotes the propeller's advance coefficient, which can be calculated by:

$$J = \frac{(1-w)\cdot V_S}{n\cdot D} \tag{10}$$

where, w *is* the wake coefficient.

The power of the propeller is provided by the main engine whose power can be expressed by the following equation:

$$P_B = \frac{R\cdot V_S}{k\cdot\eta_S\eta_G\eta_O\eta_H\eta_R} \tag{11}$$

where, η_S is transmission efficiency of the shaft; η_G is the efficiency of the gearbox; η_R is relative rotating efficiency; η_O is open water efficiency of the propeller, and η_H is the hull efficiency, which can be expressed by the following equations:

$$\eta_H = \frac{1-t}{1-w};\ \eta_0 = \frac{K_T}{K_Q}\cdot\frac{J}{2\pi} \tag{12}$$

Therefore, the final main engine power can be obtained by the following equation:

$$P_B = \frac{R\cdot V_S\cdot K_Q\cdot 2\pi\cdot(1-w)}{k\cdot\eta_S\eta_G\eta_R\cdot K_T\cdot J\cdot(1-t)} = \frac{2\pi\cdot\rho\cdot n^3\cdot D^5\cdot K_Q}{\eta_S\eta_G\eta_R} = \frac{2\pi\cdot n\cdot Q}{\eta_S\eta_G\eta_R} \tag{13}$$

Then, one can calculate the main engine's fuel consumption per unit distance, as shown in the following equation:

$$q_{main} = \frac{2\pi k\cdot n\cdot Q}{\eta_S\eta_G\eta_R\cdot(V_s \pm V_w)}\cdot g_{main} = \frac{2\pi k\cdot n\cdot f_{power}(n)}{\eta_S\eta_G\eta_R\cdot(f_{speed}(n) \pm V_w)}\cdot g_{main} \tag{14}$$

where, q_{main} denotes the main engines' fuel consumption per unit distance; V_w is the water speed; g_{main} denotes the main engine's specific fuel consumption rate; Q and V_s are functions of n:

$$Q = f_{power}(n) = K_Q \times \rho n^2 D^5 \tag{15}$$

$$V_S = f_{speed}(n) = \frac{J\cdot n\cdot D}{(1-w)} \tag{16}$$

Finally, the ship energy efficiency model considering multiple environmental factors can be established. In this model, the fuel consumption differs as a function of engine speeds and environmental conditions, which are the considered parameters here for optimizing the ship energy efficiency.

3.2.2. Non-linear optimization of engine speed

Through the established ship energy efficiency model considering multiple environmental factors, the real-time fuel consumption and sailing time corresponding to different engine speeds under various navigational environments can be obtained. In this paper, the total main engine fuel consumption through a route is taken as the objective function of optimization; the sailing time serves as the main constraint; and the segment-dependent main engine speeds are used as the optimization variables. Therefore, the established non-linear optimization model is shown below:

$$\min Q_{total} = \sum_{i=1}^{M}\left(\left(\frac{2\pi k\cdot n_i\cdot f_{power}(n_i)}{\eta_S\eta_G\eta_R\cdot(f_{speed}(n_i) \pm V_w)}\cdot g_{main}\right)\cdot S_i\right) \tag{17}$$

Subject to the following constraints:

$$T_{total} = \sum_{i=1}^{M}(S_i/f_{speed}(n_i)) < T_{\text{limit}},\ \forall\ i \in (1,..., M) \tag{18}$$

$$N_{\min} < n_i < N_{\max},\ \forall\ i \in (1,..., M) \tag{19}$$

$$V_{\min} < f_{speed}(n_i) < V_{\max},\ \forall\ i \in (1,..., M) \tag{20}$$

where, M denotes the total kinds of segments; n_i is the engine speed of the ith category of segment (r/min); S_i denotes the total distance of the ith category of segment (m); $f_{\text{speed}}(n_i)$ is the sailing speed of the ith category of segment (m/s); T_{limit} denotes the required sailing time.

3.3. Solution method based on PSO algorithm

PSO is a swarm intelligence algorithm based on iterative processes. Compared with other optimization algorithms, the PSO algorithm is easy to implement and especially suitable for handling nonlinear optimization problems (Wang et al., 2016b). With these advantages, the PSO algorithm has been effectively applied to solve a wide range of optimization problems (Kornelakis, 2010; Wang et al., 2017). Therefore, in this paper, the PSO algorithm is also adopted to solve the nonlinear optimization problem concerning the optimal engine speeds under different environmental conditions. The workflow is outlined as follows:

Step 1: Initialize N particles with M dimensions corresponding to the engine speeds of the M kinds of segments of the route; calculate fitness value of each particle using Eq. (17); determine the individual optimal value and group optimal value.

Step 2: Update the velocity and position of each particle; the location of each particle is updated according to its own velocity; the velocity and location of each particle are updated by the following equations:

$$V^{k+1} = w\cdot V^k + c_1\cdot r_1(p_{best}{}^k - X^k) + c_2 \cdot r_2(g_{best}{}^k - X^k),\ \forall\ k \in (1,..., k_{max} - 1) \tag{21}$$

$$X^{k+1} = X^k + V^{k+1},\ \forall\ k \in (1,..., k_{max} - 1) \tag{22}$$

where, k denotes the number of the current iteration; P_{best} denotes the previous optimal value; g_{best} denotes the global optimal value; X

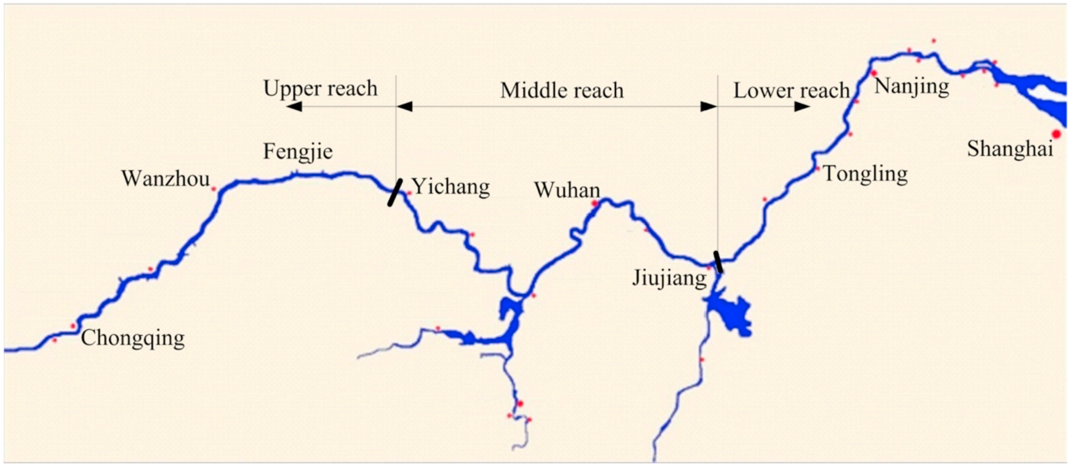


Fig. 3. Case study based on the Yangtze River.

denotes the particle location; V denotes the particle velocity; c_1 and c_2 denote the learning factors; r_1 and r_2 are random numbers between 0 and 1; and w is the inertia weight, which can be expressed as:

$$w = w_{max} - (w_{max} - w_{\min}) * iter_{current} / iter_{\max} \tag{23}$$

where, $w_{\max}$ denotes the maximum inertia factor; $w_{\min}$ denotes the minimum inertia factor; $iter_{\text{current}}$ denotes the current iteration number; and $iter_{\max}$ denotes the maximum iteration number.

Step 3: Recalculate the fitness value of each particle subject to the constraints in Eqs. (18)–(20), then update the optimal values of the individual particles and the overall population.

Step 4: Go to *Step 2* until the algorithm converges, then the optimal individual can be obtained, which gives the segment-dependent optimal engine speeds.

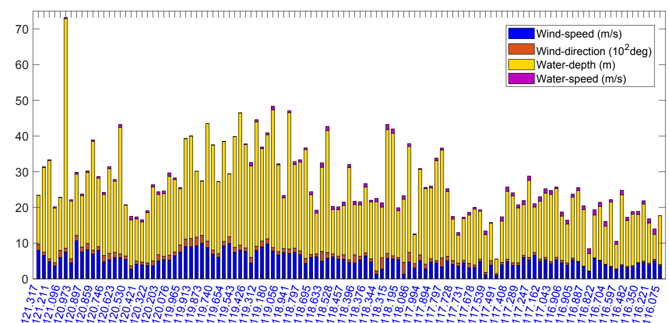
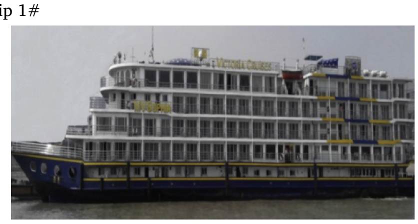


Fig. 4. Average environmental data at different locations of the lower reach.

Table 1
Data acquisition form based on the target ships.

Ships	Parameters	Values	Sensors	Data
Ship 1#	Length	80 m	Wind speed sensor	Wind speed
	Width	14.8 m	Wind direction sensor	Wind direction
	Design sailing speed	28 km/h	Water depth sensor	Water depth
	Gross tonnage	4587 t	Water speed sensor	Water speed
	Design draft	2.7 m	Shaft power tester	Speed and torque
	Engine power	960 kW × 2	GPS receiving device	Sailing speed
	Engine speed	750 rpm	Fuel consumption sensor	Fuel consumption
Ship 2#	Length	90 m	Wind speed sensor	Wind speed
	Width	16.16 m	Wind direction sensor	Wind direction
	Depth of the ship	6 m	Water depth sensor	Water depth
	Gross tonnage	5270 t	Water speed sensor	Water speed
	Main engine	8190ZLC-1	GPS receiving device	Sailing speed
	Engine power	720 kW × 2	Shaft power tester	Speed and torque
	Engine speed	1450 rpm	Fuel consumption sensor	Fuel consumption
Ship 3#	Length	107 m	Doppler velocity log	Ship speed to water
	Width	17.2 m	Speed tester	Engine speed
	Design sailing speed	9.5 kn	GPS receiving device	Sailing speed
	Gross tonnage	4559 t		
	Design draft	4.0 m		
	Engine power	518 kW × 2		

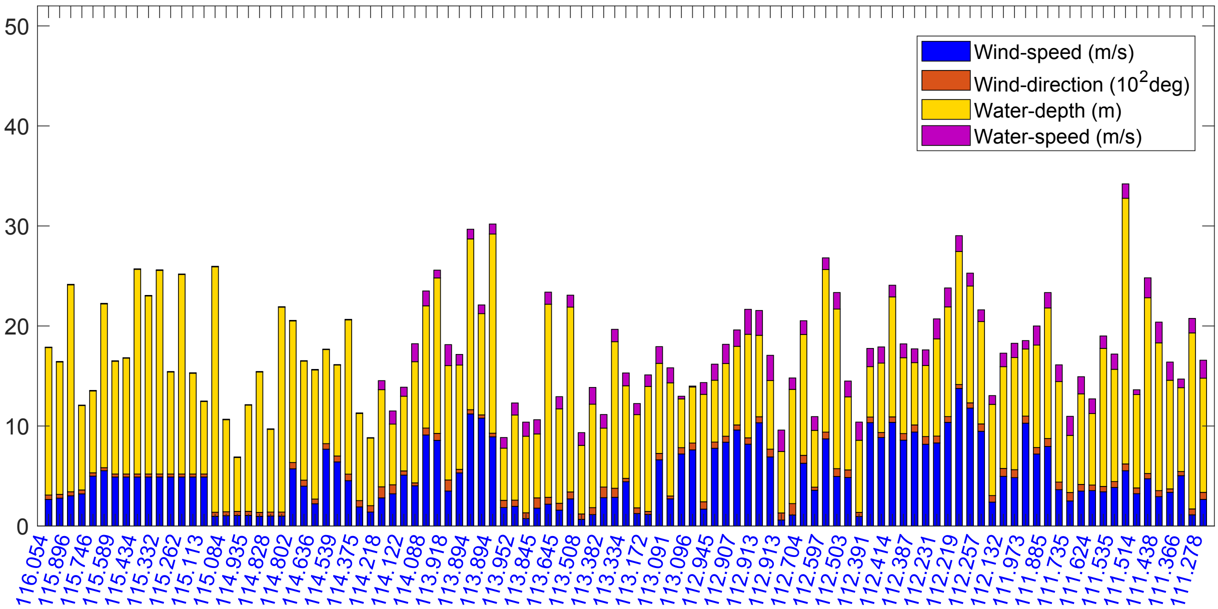


Fig. 5. Average environmental data at different locations of the middle reach.

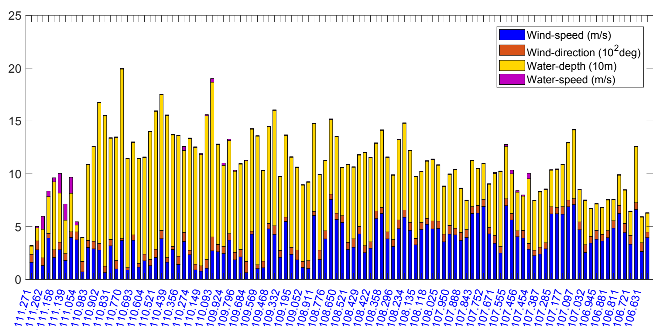


Fig. 6. Average environmental data at different locations of the upper reach.

4. Case study

The present case study is based on the Yangtze River, the longest river in China. The Yangtze River has three reaches, namely upper, middle and lower reaches, as shown in Fig. 3. The upper reach has a river bed with a huge drop ratio; the middle reach has a multi-bridge tortuous waterway with small water depth; and the lower reach has a gentle environment. The navigational characteristics of different reaches are strongly season-dependent. Therefore, the present study splits the entire route into three reaches, and conducts analysis based on the dry season and the rain season separately.

4.1. Data acquisition and preprocessing

The data concerning the ship energy efficiency optimization can be divided into two categories 1) the operational data, including sailing speed, position, engine speed, and fuel consumption; 2) the environmental data, including wind speed, wind direction, water depth, and water speed. These data points are collected through onboard sensors, part of which are shown in Table 1 with the corresponding parameters also illustrated in the table. The collected data covers different segments and working conditions spanning the all three reaches of the

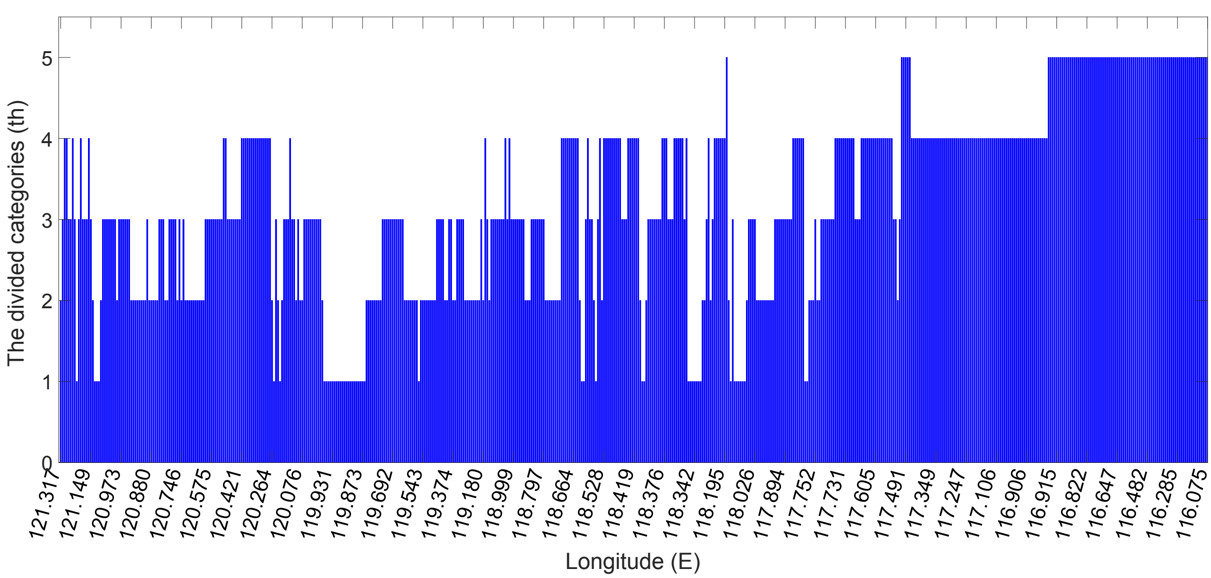


Fig. 7. Categories of environment at different locations of the lower reach (Dry season).

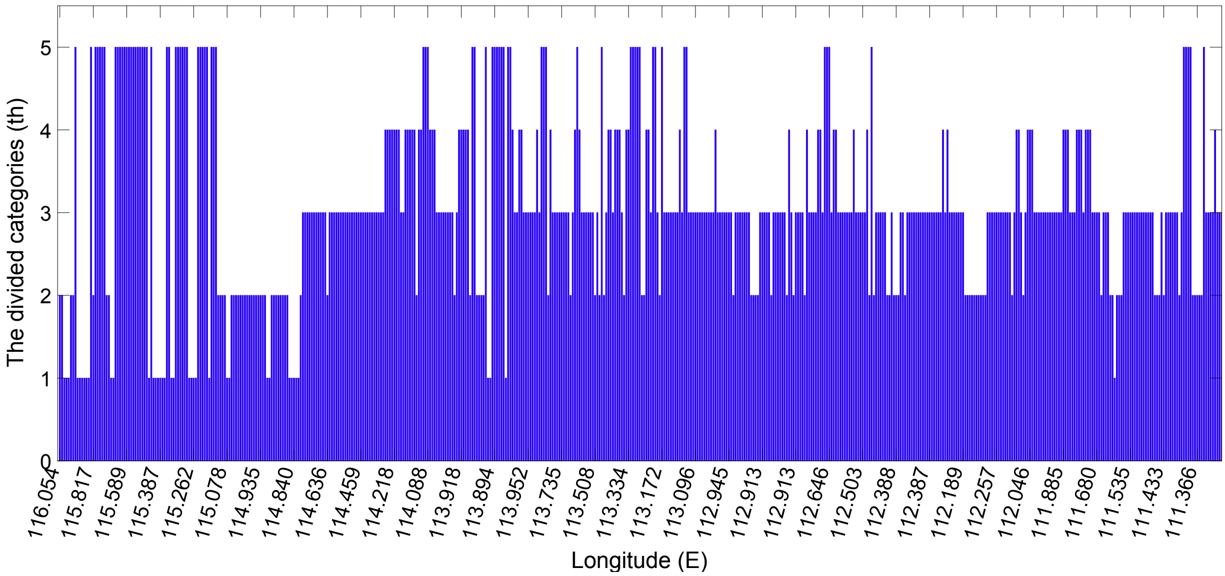


Fig. 8. Categories of environment at different locations of the middle reach (Dry season).

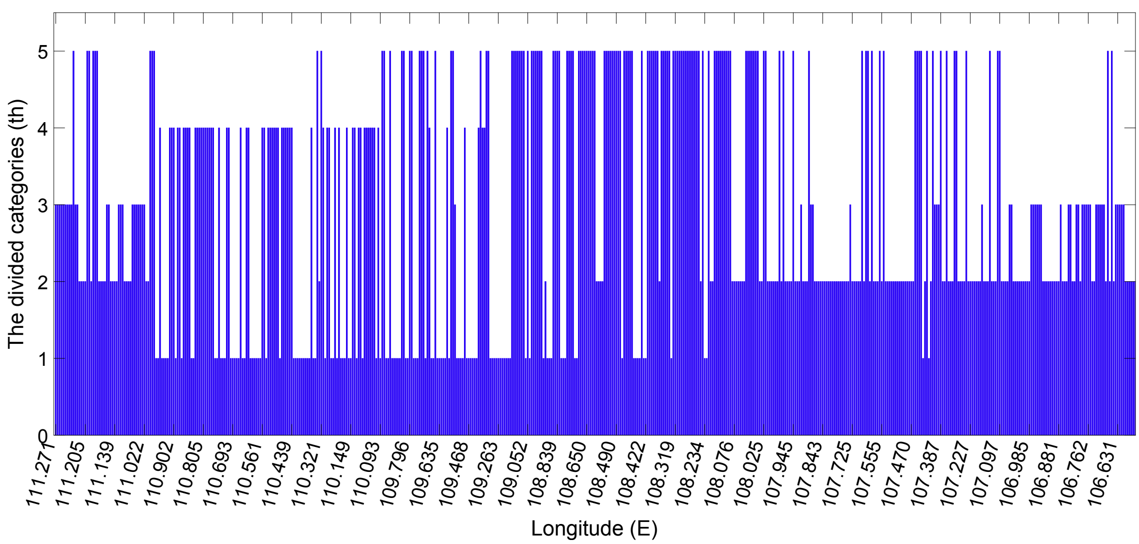


Fig. 9. Categories of environment at different locations of the upper reach (Dry season).

Table 2
The environmental characteristics of different segments - Dry season.

Items	Lower reach					Middle reach					Upper reach				
Segments	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Water depth (m)	21.1	24.9	21.9	17.9	13.9	21.3	10.6	10.3	10.1	10.8	94.5	38.6	23.0	126	66.1
Water speed (m/s)	0.50	0.49	0.60	0.90	1.01	0.16	0.96	1.20	1.40	0.65	0.07	0.16	0.26	0.08	0.10
Wind direction (deg)	262	159	107	71.9	27.9	35.2	44.5	66.4	91.4	30.5	52.4	63.7	79.6	80.2	71.1
Wind speed (m/s)	6.52	6.63	5.82	4.59	3.76	3.76	4.44	5.54	3.09	4.80	2.96	4.44	3.27	1.99	3.75

Yangtze River. The sampling frequency is once per second, leading to 800 K samples per trip. Over the last four years, a large number of data points concerning environmental and operational information were obtained. In addition, the technical and operational parameters were obtained from an on-shore information center.

Upon the completion of data collection, the next important procedure is the data preprocessing. To analyze the characteristics of the navigational environment, the data points concerning water speed, water depth, wind speed, wind direction, longitude, and latitude are retrieved from the database. The data preprocessing stage starts with the removal of low-quality data points, e.g., those with missing values (Han, 2012), aiming to enhance the data quality. In practice, this operation does not result in a massive loss of data, as the removed data points only accounts for less than 0.5% of the overall dataset. Besides, the incomplete and obviously abnormal data points are replaced by the linearly interpolated values (Yin and Zhao, 2017). In addition, the water velocity is obtained by computing the difference between the ship speed to ground and the ship speed to water. Similarly, the absolute wind speed can be obtained from the difference between the relative wind speed and the ship speed to ground. Finally, we collect data

Table 3
Ship energy efficiency optimization results - Dry season.

Items		Lower reach					Middle reach					Upper reach				
Segments		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Engine speed (r/min)	Original	551.35	560.12	561.81	570.28	585.05	608.58	600.58	601.20	599.19	609.97	541.12	564.91	457.40	509.43	573.73
	Optimal	577.04	579.76	570.55	548.53	546.07	638.10	597.31	589.47	581.77	609.27	539.64	540.34	541.34	544.04	535.94
Sailing speed (m/s)	Original	4.988	4.965	5.073	4.913	4.936	5.695	5.167	5.162	5.152	5.218	5.192	5.374	4.498	4.945	5.445
	Optimal	5.208	5.139	5.148	4.742	4.639	5.899	5.147	5.091	5.046	5.214	5.180	5.184	5.201	5.222	5.155
Fuel consumption (g/m)	Original	8.960	9.598	9.585	11.575	13.057	11.648	15.532	16.563	17.289	15.085	10.464	11.751	7.432	9.116	12.027
	Optimal	9.970	10.364	9.934	10.584	11.182	13.168	15.319	15.771	16.080	15.041	10.399	10.621	10.855	10.593	10.291
CO_2 emission (g/m)	Original	28.726	30.771	30.730	37.110	41.860	37.342	49.795	53.102	55.427	48.364	33.548	37.673	23.827	29.225	38.560
	Optimal	31.965	33.228	31.849	33.934	35.850	42.217	49.114	50.563	51.553	48.222	33.340	34.050	34.802	33.960	32.994

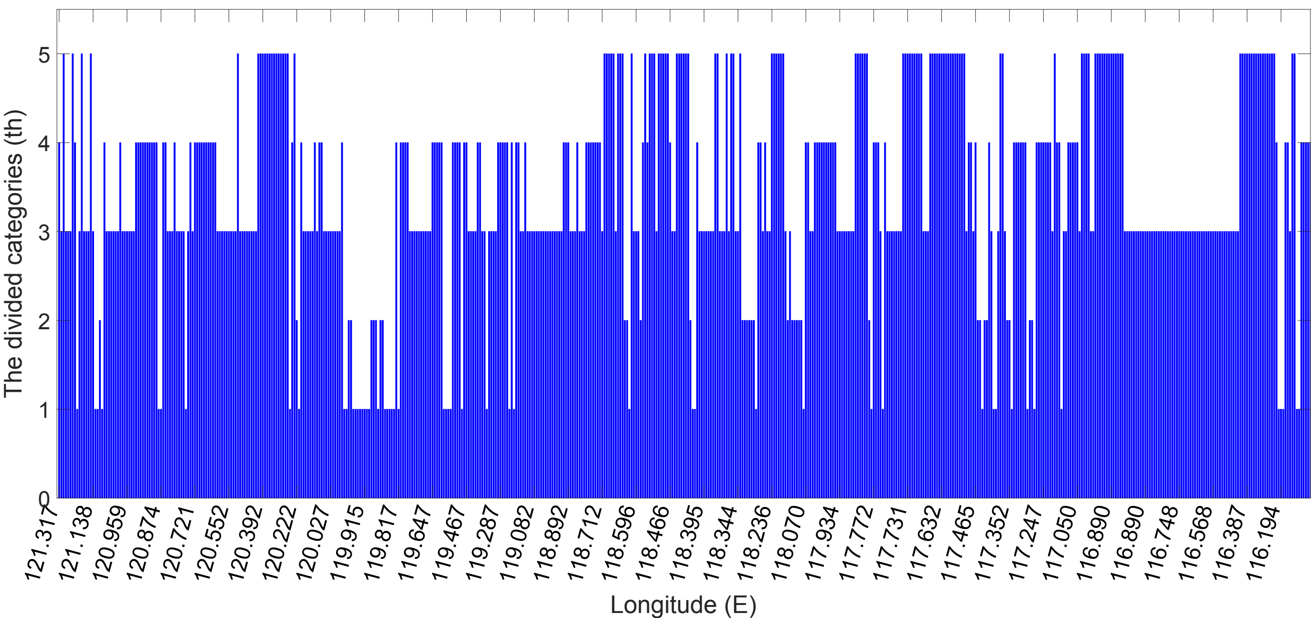


Fig. 10. Categories of environment at different locations of the lower reach (Rain season).

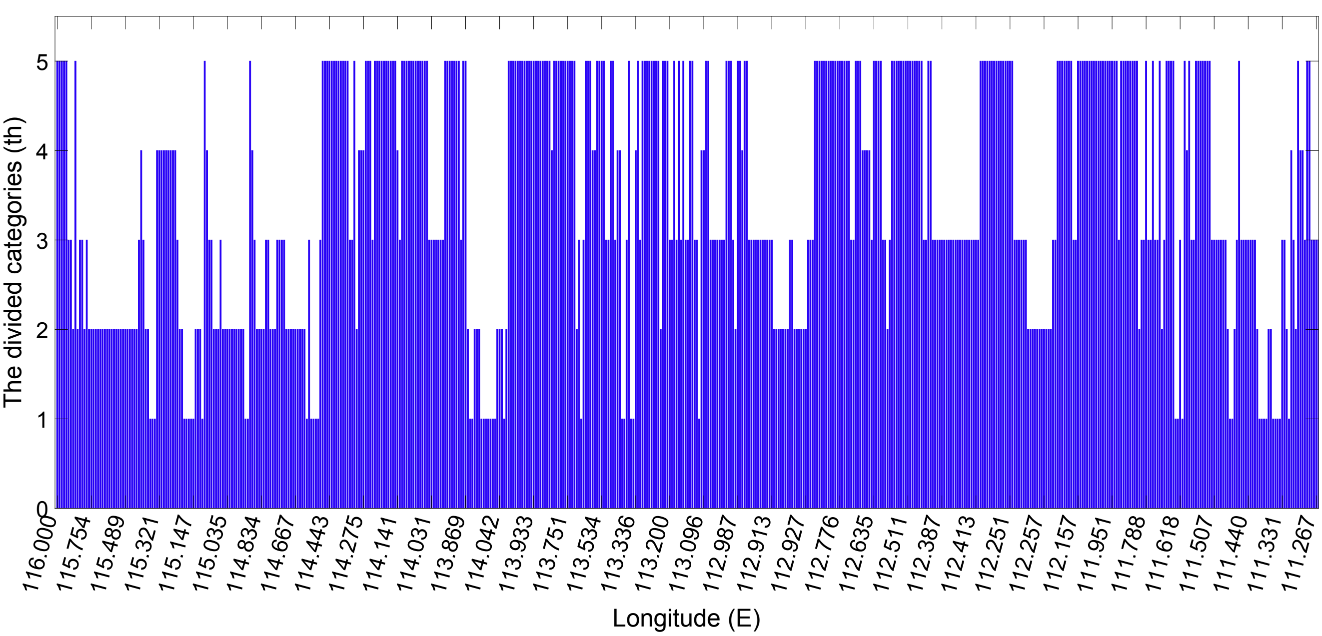


Fig. 11. Categories of environment at different locations of the middle reach (Rain season).

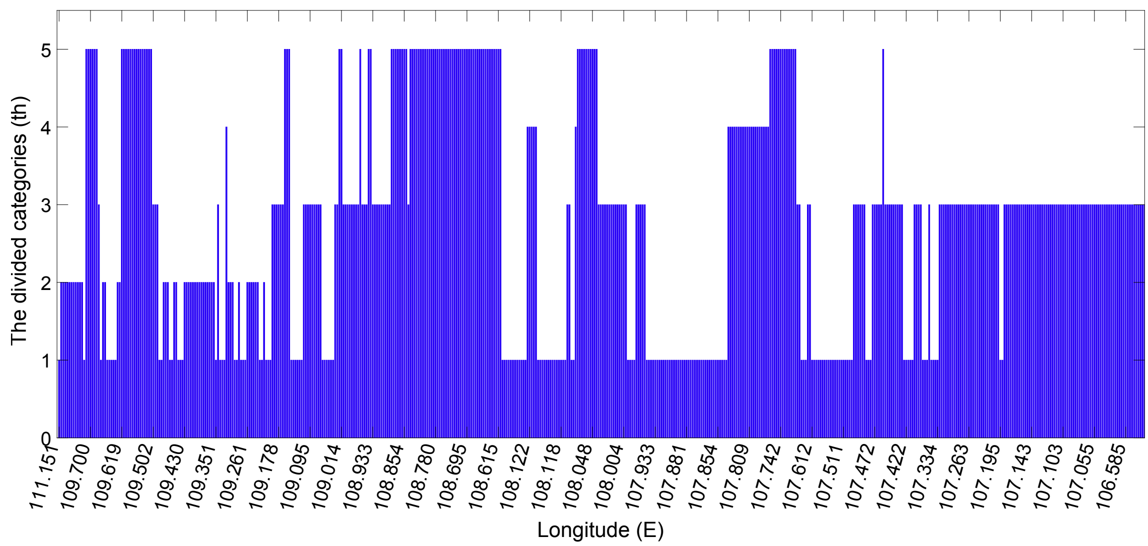


Fig. 12. Categories of environment at different locations of the upper reach (Rain season).

Table 4
The environmental characteristics of different segments - Rain season.

Items	Lower reach					Middle reach					Upper reach				
Segments	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Water depth (m)	21.4	18.4	20.8	22.7	17.8	15.5	15.7	15.5	18.3	14.2	31.8	62.5	29.7	20.0	48.1
Water speed (m/s)	0.35	0.59	0.56	0.49	0.62	0.75	0.82	1.26	0.87	1.31	0.83	0.43	1.28	1.10	0.41
Wind direction (deg)	209	292	102	153	71	53	80	113	183	141	213	296	173	293	128
Wind speed (m/s)	7.00	5.27	4.87	5.68	3.92	3.87	5.03	5.43	2.56	4.13	4.30	5.24	3.54	5.14	2.93

Table 5
Ship energy efficiency optimization results - Rain season.

Items		Lower reach					Middle reach					Upper reach				
Segments		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Engine speed (r/min)	Original	563.04	553.15	572.77	559.71	586.21	590.78	600.22	588.18	570.32	584.49	558.36	455.87	566.85	593.85	480.50
	Optimal	586.67	575.25	566.92	578.53	553.42	593.90	583.54	578.48	592.22	576.98	529.18	530.45	533.35	589.30	546.33
Sailing speed (m/s)	Original	4.994	4.996	5.171	4.996	5.034	5.245	5.319	5.230	5.408	5.167	5.303	4.468	5.369	5.587	4.691
	Optimal	5.200	5.185	5.122	5.160	4.782	5.265	5.211	5.166	5.570	5.117	5.072	5.102	5.107	5.554	5.232
Fuel consumption (g/m)	Original	9.406	9.239	9.912	9.463	11.559	16.259	17.018	18.141	13.932	18.377	13.258	7.740	15.169	15.923	8.632
	Optimal	10.324	10.116	9.678	10.201	10.087	16.452	15.982	17.513	15.111	17.886	11.835	10.796	13.419	15.665	11.465
CO_2 emission (g/m)	Original	30.155	29.621	31.777	30.339	37.057	52.128	54.560	58.159	44.665	58.918	42.504	24.815	48.633	51.049	27.673
	Optimal	33.098	32.433	31.026	32.704	32.339	52.746	51.239	56.145	48.445	57.343	37.944	34.612	43.021	50.221	36.755

Table 6
Comparative analysis for different reaches in different scenarios.

Season	Original		Optimal		Reduction		
	Fuel consumption	CO_2 emission	Fuel consumption	CO_2 emission	Fuel consumption	CO_2 emission	Reduced percent
Lower reach (kg)							
Dry season	9679	31031	9442	30272	237	759	2.45%
Rain season	9198	29487	9085	29126	113	361	1.22%
Middle reach (kg)							
Dry season	15090	48380	14640	46937	450	1443	2.98%
Rain season	18235	58462	17742	56880	493	1582	2.70%
Upper reach (kg)							
Dry season	8636	27687	8320	26675	316	1012	3.66%
Rain season	8010	25680	7771	24915	239	765	3.00%
The entire route including the above three reaches (kg)							
Dry season	33405	107096	32402	103880	1003	3216	3.00%
Rain season	35443	113630	34598	110921	845	2709	2.38%

concerning ship operation and environmental factors, which are partly shown in Figs. 4–6, spanning different reaches of the Yangtze River.

4.2. Scenario A: dry season

4.2.1. Route division based on the distributed k-means algorithm

Based on the aforementioned distributed k-means algorithm and the data processing method, the present study sets the initial number of clusters to 5 and the maximum number of iterations to 15. In addition, the Squared Euclidean Distance method is adopted here for measuring distances. Considering the fact that the commonly used engine speeds have five different levels, the present model divides the route into five types of segments so as to reduce the fluctuation of engine speed.

According to the clustering result, the data points with similar environmental conditions can be put into the same type of segment. The five types of segments obtained here are labeled as 1 through 5, which are in turn distributed over different segments of the route, as shown in Figs. 7–9.

4.2.2. Energy efficiency optimization based on route division

In this section, a cruise ship sailing in the Yangtze River is modeled as the target ship. Based on the results of route division, the environmental characteristics of different segments are obtained by statistical analyses. For three different reaches, the average water depth, water speed, wind direction, and wind speed for different segment categories in the dry season are obtained, as shown in Table 2. According to the characteristics of navigational environment in different divisions, the aforementioned PSO algorithm is used to determine the optimal engine speed in each category of navigational environment, based on the established non-linear optimization model in **Section** 3. Here, 50 particles are initialized in the population. Each particle has five dimensions, corresponding to the optimal engine speeds of the five different kinds of segments.

The algorithm converges after a number of iterations, giving the optimal fitness value, i.e., the total fuel consumption of the entire reach. The obtained optimal engine speeds in different segment categories for the three reaches are shown in Table 3. In addition, the field data (i.e., sailing speed, fuel consumption, and CO_2 emission) for the original engine speeds and the optimal engine speeds are illustrated in Table 3. The results show that in some segments, the optimized engine speeds exceed the original engine speeds, while in some others, the optimized engine speeds are below the original engine speeds. That is the main reason why the fuel consumption and CO_2 emissions can be reduced effectively by adopting this optimization method considering multiple environmental factors.

4.3. Scenario B: rain season

4.3.1. Route division based on the distributed k-means algorithm

Similar to the Scenario A, the same distributed k-means algorithm is used to determine the route division based on the environmental factors in the rain season. According to the clustering result, the obtained total five types of segments are distributed in different locations of the route, as shown in Figs. 10–12.

4.3.2. Energy efficiency optimization based on the route division

Based on the route division results, the environmental characteristics of different segments are obtained by statistical analyses. For the three different reaches, the average water depth, water speed, wind direction, and wind speed for different segment categories in the rain season are obtained, as shown in Table 4. According to the characteristics of the navigational environment in different divisions, the PSO algorithm is used to determine the optimal engine speed for each category of navigational environment based on the established non-linear optimization model in **Section** 3.

The algorithm converges after a number of iterations, with the optimal fitness value generated, i.e., the total fuel consumption of the entire reach. The obtained optimal engine speeds in different segment categories for the three reaches are shown in Table 5. The field data (i.e., sailing speed, fuel consumption, and CO_2 emission) for the original engine speeds and the optimal engine speeds are also illustrated in Table 5. The results show that the optimal engine speeds differ from the original engine speeds in different segments with different environmental characteristics, which is the main reason why the fuel consumption and CO_2 emissions can be reduced effectively by adopting the present optimization method considering multiple environmental factors.

4.4. Comparative analysis

The final results for different reaches in the dry and rain seasons are shown in Table 6. For the lower reach of the Yangtze River in the dry season, the total reduction in fuel consumption is 237 kg, compared with the practical navigation method. Given that the CO_2 conversion rate of the diesel fuel is 3.206 (Burel et al., 2013), the reduction in CO_2 emissions can reach 759 kg using the present optimization method, corresponding to a change of 2.45%. As for the middle reach, the optimization yields 450 kg of reduction in fuel consumption and 1443 kg of reduction in CO_2 emission, corresponding to a change of 2.98%. When it comes to the upper reach of the Yangtze River, the present optimization leads to the highest reduction in fuel consumption and CO_2 emission, with a change of 3.66%, i.e., the total amount of fuel reduction is 316 kg and the total amount of reduction in CO_2 emission is 1012 kg for the dry season.

Similarly, for the rain season, the reductions in fuel consumption and CO_2 emission are 113 kg and 361 kg, respectively, corresponding to a change of 1.22% for the lower reach. As for the middle reach, this optimization method can reduce fuel consumption and CO_2 emission by about 2.7%, corresponding to 493 kg and 1582 kg, respectively. When it comes to the upper reach of the Yangtze River, the change can reach 3%, with the reduction in fuel consumption and CO_2 emission reaching 239 kg and 765 kg, respectively.

By comparing the optimization results of these three different reaches, one can see that the upper reach appears to be superior to the middle and lower reaches in terms of how much enhancement of ship energy efficiency the optimization can bring about. This is likely caused by the fact that, compare to the middle and lower reaches, the upper reach of the Yangze River has a larger drop ratio of river bed and the two dams (the Gezhou dam and Three Gorges dam), which leads to a larger difference in the environmental factors associated with different segments. The complex environmental conditions provide more potential for speed optimization and fuel saving, as it is difficult to determine the optimal engine speeds manually. Following the same logic, one can explain why the middle reach is superior to the lower reach in terms of how much enhancement of ship energy efficiency the optimization can bring about: the waterway in the middle reach are more complex than that in the lower reach due to the presence of narrow and complex channels, leading to a larger difference in the environmental factors associated with different segments. By contrast, the small variation of environmental factors in the lower reach leads to the lowest room for optimizing the energy conservation and emission reduction there.

For the entire route including the upper, middle and lower reaches, the total amount of reduction in fuel consumption per trip is 1003 kg in the dry season and 845 kg in the rain season. Meanwhile, this optimization effort can undoubtedly improve the profit margin of shipping companies as driven by the fuel conservation. Such improvement is significant for a shipping company, especially in an era with the recession of shipping industry.

5. Conclusions and future research

In this paper, an attempt has been made to optimize ship energy efficiency through big data analysis in the field of waterway transport. The route division based on the environmental data analysis is achieved and the ship navigation optimization method based on the route division is proposed. The case study on the Yangtze River demonstrates the applicability of this method. It can reduce the ship's fuel consumption and CO_2 emission over the entire route by around 3% and 2.38% in the dry and rain seasons, respectively. The percentage of reduction can reach 3.66% under complex environmental conditions for the upper reach in the dry season.

The proposed optimization method can also be applied to other types of ships and other inland rivers such as the Rhine River, so long as the related data is available. Building a data-driven energy efficiency model considering multiple influencing factors will be the next step of our research. In addition, one can further extend the present optimization method to handle the energy efficiency optimization of a ship fleet. Such extension will involve much more influencing factors, such as ship parameters, route characteristics, port operation and transport demand. Besides, one needs to consider the correlation among these factors as well as the coordination between ships. Therefore, the future research will focus on modifying the present energy efficiency optimization method so as to provide a theoretical foundation for the ship fleet energy efficiency optimization.

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