RESEARCH ON ENERGY-SAVING ROUTE OPTIMIZATION BASED ON DYNAMIC FUEL CONSUMPTION MODEL OF SHIP

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This paper provides a new approach based on the ship's dynamic fuel consumption to further improve the level of energy-efficient of ship route. Firstly, the factors related to fuel consumption are selected through analyzed from navigation area. Then, an instantaneous fuel consumption model of the ship is established with these selected factors. Next, a virtual grid model of sea is established, and an optimal ship route is designed by adopting the improved ant colony algorithm. Finally, it is concluded that the energy-saving route optimization based on dynamic fuel consumption model has higher energy efficiency than other routes.

Keywords: Route Optimization; Dynamic Fuel Consumption Model; Ant Colony Algorithm

1. Introduction

Route planning is an important part of the ship navigation process [1]. Ship route planning is used to lay out the optimal route from departure to destination according to factors such as the shortest distance, the shortest time or the least energy in a certain obstacle environment [2]. At present, the method for most ship's global route planning is to find out the shortest route only avoiding obstacles in the ocean, in which many important factor is discounted. On the other hand, in many cases, the routing systems are based on a predefined list of routes, without a search in real time [3]. In fact, due to the complexity and variability of the marine environment, including winds and waves, the ship route directly affects the energy consumption level of ship, and needs constant readjustment accordingly. Therefore, it has great significance to design the optimal ship route in accordance with the ship energy consumption, which is most economical for the navigation of the ship [4]. On this basis, the dynamic planning of ship's route is conducive to the development of the shipping economy and the full utilization of resources.

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In various navigation routes, there are many factors affecting the fuel consumption of the ship, which includes a complex and comprehensive category such as oil, machine, and environment. As early as the 1980s and 1990s, both domestic and foreign scholars had tried to find the corresponding relationship between ship fuel consumption and various factors in navigation environment by theoretical analysis. For instance, calculating the relationship between fuel consumption and speed [5] as well as segmenting and simplifying the route to realize the optimization of each segment and establish an optimal scheduling model. Some researchers also took the external factors that would change in real-time during the navigation process into consideration. Researchers such as *Xiaodong Meng* took into account the influence of wave on consumption by introducing additional fuel consumption [6], which improved the accuracy of the model. *Bialystocki* proposed a simple algorithm by analyzing the correlation between fuel consumption and factors such as displacement, weather, hull and propeller roughness [7]. As a result, he verified the feasibility of the algorithm through practical exercises. Such optimized models based on theoretical formula can provide a reference for the establishment of most ship fuel consumption models. It can also optimize the models by reasonably selecting theoretical formulas or related parameters for different ship types.

Based on the above study, this research takes a comprehensive consideration of individual factors in ship route planning according to the influence of navigation conditions on fuel consumption under different routes [8]. Due to the difficulty of solving some global optimization problems from a variety of scientific and engineering fields, in the last decades some modern optimization algorithms inspired from nature were developed, one of which is swarm intelligence algorithms that can be briefly defined as the collective intelligent behavior of self-organized swarms of individuals (bird flocks, fish schools and colonies of social insects such as termites, ants and bees) [9]. Therefore, this research establishes a fuel consumption model based on navigation environment factors, and an optimal route is planned based on the modified ant colony algorithm to ensure that the ship sails under relatively high energy efficiency. As a result, the operating costs of shipping company can be effectively lowered.

2. Data Processing

2.1 Data source selection

The example ship used in the research is the Danish passenger roller *MS Smvril*, sailing on the route from *Tórshavn* to *Suðuroy*, the capital of Faroe Islands. It takes about one hour and 55 minutes to travel for a single trip. The route runs 2-3 times a day. A variety of sensors are installed in different parts of *MS Smyril* to collect various parameters during operation (parameters are shown in Table 1). And the collected data for 246 voyages from February to April in 2010 was published [10]. These parameters directly or indirectly affected fuel consumption, thus affecting the planning of the optimal route. This study will select several key parameters that have the greatest impact on fuel consumption from these parameters to form the fuel consumption model.

Table 1

Parameters collected from *MS Swvril*

No.	Parameter	No.	Parameter
1	Fuel density	11	Port rudder angle
2	Fuel temperature	12	Speed over ground (SOG)
3	Fuel volume flow rate	13	Starboard propeller pitch
4	Inclinometer trim angle	14	Starboard rudder angle
5	Latitude	15	Track degree magnetic
6	Longitude	16	Track degree true
7	Port level measurements	17	True heading
8	Starboard level measurements	18	Wind angle
9	Speed through water (STW)	19	Wind speed
10	Port propeller pitch	20	Wave scale

Focusing on this database, a series of researches are carried out by domestic and foreign researchers. In these researches, *Rui Ye* and *Jinsong Xu* adopted artificial neural networks to build a black-box model [11]. However, there are too many input variables of this model, which has poor robustness. *Jóan Petur Petersen•Daniel J* and *Jacobsen•Ole Winther* compared the differences between GP Model and ANN Model on the basis of this database [12]. They summed up the advantages and shortages of these two models and led the way for later comers.

2.2 Data truncation and vector processing

It can be seen from the raw data that since the time is not synchronized, the number of the data collected by each sensor is not the same, ranging from 548292 to 3979774. Obviously, such huge data cannot be used directly to build the model. As there is a time stamp in the data, this study cuts the data every 3 minutes, and figure out the feature quantity of the data by calculating the mean and variance of the parameters collected every 3 minutes. The equations as following:

$$\omega_{mean}(u) = \frac{1}{M}\sum_{n=0}^{M} x_n \tag{1}$$

$$\omega_{var}(u) = \frac{1}{M}\sum_{n=0}^{M-1}(x_n - \omega_{mean}(u))^2 \quad (2)$$

In the Eq. 1, $\omega_{mean}(u)$ calculates the average value of parameter u every three minutes; M represents the number of data points every three minutes; and x_n represents the value of the data point. In the Eq. 2, $\omega_{var}(u)$ represents the deviation of data from all data in three minutes.

The feature quantity obtained through the above calculation also has an order of magnitude difference between the dimensions. To eliminate these differences, the data must be standardized. The standard formula is as follows:

$$\tilde{x}_i^k = \frac{x_i^k - \bar{x}_i}{\sigma_i} \quad (3)$$

In the equation, $\tilde{x}_i^k$ is the standard data of point k in the *i-th* dimension; x_i^k is the original data of point k in the *i-th* dimension; σ_i is the standard deviation of point k in the *i-th* dimension and $\bar{x}_i$ is the mean of point k in the *i-th* dimension.

Some parameters collected in Table 1 like the wind is vector data. So, it should be processed to projection wind [13] acts on the ship directly. The action principle is shown in Fig. 1.

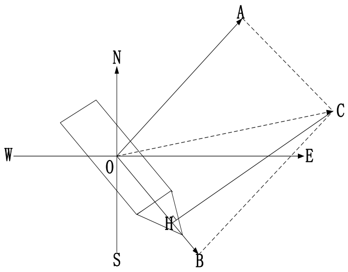

Fig. 1 Projection of wind acting on the ship

In Fig. 1, the east orientation is set as the basic direction. $\angle BOE$ refers to the heading and $\angle AOE$ indicates the wind direction measured on the ship. According to the vector algorithm: $\overrightarrow{OC} = \overrightarrow{OA} + \overrightarrow{OB}$, $\overrightarrow{OC}$ refers to the earth wind, whose wind direction is toward the ground. The pedal of $CH \perp OB$ is H, the $\overrightarrow{OH}$ is the projection of the natural wind which directly acts on the hull.

3. Establishment of Dynamic Fuel Consumption Model

3.1 Working conditions affecting fuel consumption

The changes in environment will cause changes in fuel consumption in the process of ship navigation. To understand the relationship between these working conditions, environmental factor and fuel consumption, we select a complete voyage in the database to draw the relationship between various factors and fuel consumption as shown in Fig. 2. The fuel consumption data, the rudder data, the pitch data are the standardized data, and the projection wind data is the data obtained by the vector processing of the wind data measured on the ship.

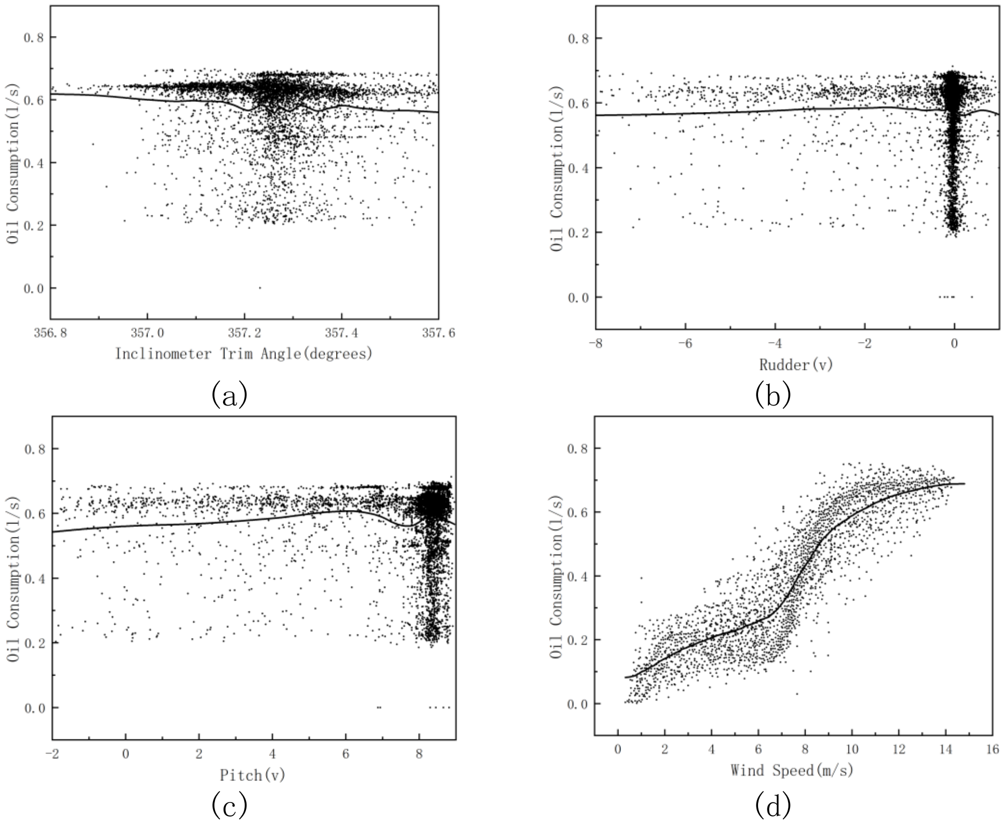

Fig. 2 Relationship between various factors and fuel consumption

In Fig. 2, each factor has an impact on fuel consumption. The most important factor is the projection wind. It can be seen from Fig. 2(d) that, when the wind speed is less than 6 m/s, the change of fuel consumption changes along with the projection wind speed is not obvious and fluctuates within a small range; when the wind speed exceeds 8m/s, the fuel consumption increases rapidly with the increase of the projection wind speed.

3.2 Establishment of dynamic fuel consumption model for ships

To get closer to the actual engineering application, environmental factors such as wind, wave and current need to be considered in the fuel consumption model. In view of the unclear function form of specific speed-fuel consumption, how to find the trend of scatter points and make efficient fitting under the premise of the fuzzy function form is the focus of current research. To some extent, semi-parametric fitting is a good choice. It originates from the extension of the non-parametric fitting, and its essence is to use spline interpolation and introduce random effect to construct a mixed effect model to solve the fitting form under the unknown function form [14]. The mixed-effect model of the semi-parametric fitting is as follows.

$$Y_m = f(x_i) + \beta_2 P_i + \beta_3 R_i + \beta_4 I_i + \beta_5 W_i + \beta_6 B_i + \varepsilon_i \qquad i = 1,2,3 \ldots\ldots \tag{4}$$

In Eq. 4, Y_m represents fuel consumption and i represents the i-*th* sample observation; $P, R, I, W,$ and B respectively represent pitch, rudder angle, draft depth, projection wind, and wave; $\beta_{2\sim6}$ refers to the influence level of pitch, rudder angle, draft depth, projection wind, and wave on fuel consumption. $f(x_i)$ represents the functional relationship between ship fuel consumption and speed to be estimated. The estimated function is decomposed by spline interpolation to establish a mixed effect model:

$$f(x_i) = \beta_0 + \beta_1 x_i + \sum_{k-1}^{K} (x_i - \kappa_k)_+ \tag{5}$$

$$(x_i - \kappa_k)_+ = \begin{cases} x_i - \kappa_k & x_i > \kappa_k \\ 0 & x_i \leq \kappa_k \end{cases} \tag{6}$$

In the Eq. 5, $f(x_i)$ is the concrete expression of $f(x_i)$ in Eq. 4. β_0 is a constant to adjust the accuracy of the model, and β_1 is the coefficient of the independent variable(speed). The value of $(x_i - \kappa_k)_+$ depends on the formula Eq. 6. κ_k is the k-*th* quantile of the selected node vector, $k = 1,2,3 \ldots K$. Based on historical experience and the sample size, take the $K = \min\left(35, {}^4/_n\right)$; By substituting linear splines, the Eq. 4 can become of Eq. 5 as follows:

$$Y_m = \beta_0 + \beta_1 x_i + \sum_{k-1}^{K} (x_i - \kappa_k)_+ + \beta_2 P_i + \beta_3 R_i + \beta_4 I_i + \beta_5 W_i + \beta_6 B_i + \varepsilon_i \tag{7}$$

Based on the processed data from the database of the ship *MS Smvril*, the parameters $\beta = [\beta_0\ \beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_5\ \beta_6]$ may be calculated by the maximum likelihood estimation (MLE) to indicate the quantitative influence of various impact factors (i.e. pitch, rudder angle, draft depth, projection wind, and wave) on fuel consumption. Furthermore, the fitting-figure of dynamic fuel consumption model can be obtained based on Eq. 7. The figure and the processed partial sample data are shown in Fig. 3.

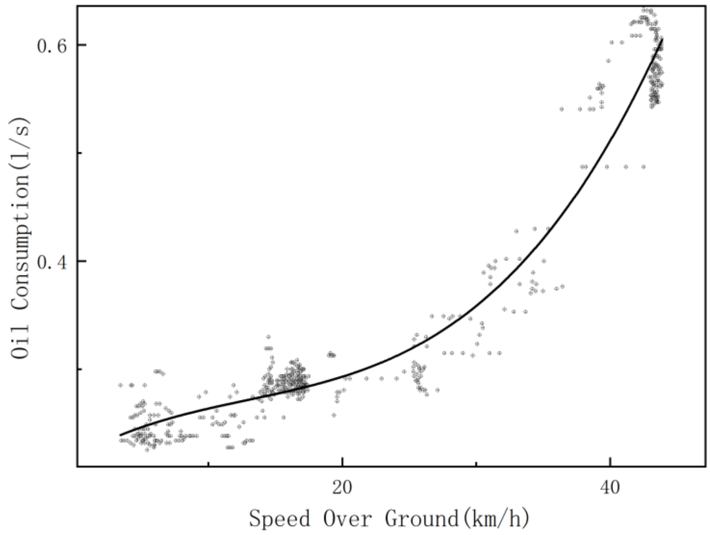

Fig. 3 Fitting result of dynamic fuel consumption model

It can be seen from Fig. 3 that the fitting results are very close to the cubic relationship model of experience data, indicating that the modified model is very ideal. For the convenience of the following description, this study will introduce the modified model of working and environment condition coefficient as W&E Condition Fuel Consumption Model.

4. Establishment of Marine Environment Model

To model the environment of the *Faroe Islands*, a grid method is used to express the environment [15]. Its principle is to divide the environmental map information into two-dimensional grids of a certain size evenly and to complete the spatial environment modeling by defining grids. Fig.4 shows the sea environment of the *Faroe Islands* (picture taken from Google Maps). Rasterization is performed on the basis of this sea environment, and a 50×50 square matrix is established. It is stipulated that if the center of each grid is an island, the grid is an obstacle grid, and if it is a sea area, it is a free grid. Under the influence of W&E conditions, the free grid can be changed into a W&E condition grid regarded as a dynamic obstacle grid. The rasterized marine environment of *Faroe Islands* sea is shown in Fig. 5.

In Fig. 4, *MS Smyril* needs to go back and forth from position ① to position ②, corresponding to the position in Fig. 5 is from (25.5, 40.5) to (24.5, 0.5). In Fig. 5, the grids with gray shadows are obstacle grids, the grids with transparent backgrounds are free grids.

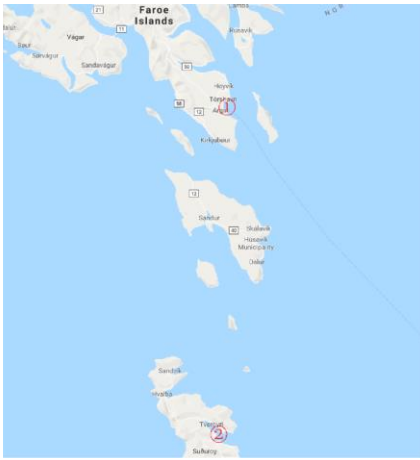

Fig. 4 Sea area of Faroe Islands

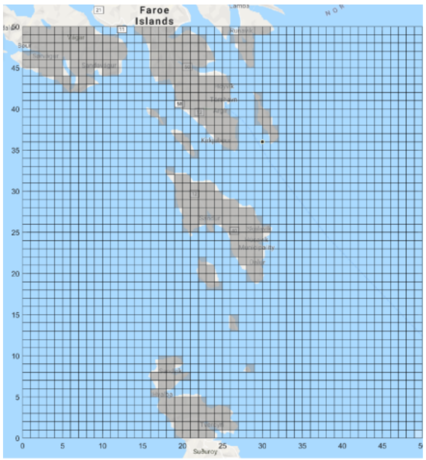

Fig. 5 Sea area after Rasterization

According to the influence of wind, wave and other factors on the fuel consumption of the ship, the free grids of the sea can be modified to establish a virtual grid model, also known as the W&E condition grids. In the model, the information of wave amplitude, current velocity, wind speed, and direction stored in each grid is taken as the attributes of the grids [16]. The fuel consumption of the ship passing through the virtual grids can be obtained by substituting these attributes into the instantaneous fuel consumption model as shown in Eq. 7. The virtual grids that considers the impact on energy consumption of environmental factors is changeable. For example, there are a threshold value of fuel consumption in Eq. 7, when Y_m is greater than threshold value under certain condition, the W&E condition grids become a W&E obstacle grids, so other routes should be explored to change the W&E condition for energy-saving.

5. Ship Route Design Based on Dynamic Fuel Consumption Model

5.1 Modification of Ant Colony Algorithms

Based on the characteristics of the marine environment model, the Ant Colony Algorithm (ACA) [17] can be used for navigation route planning, which simulates the foraging behavior of ants in nature. In the process of searching for food, ant's walking path is used to express the feasible solution of the problem to be optimized, and all the paths of the whole ant colony constitute the solution space of the problem to be optimized. Ants with shorter paths release more pheromones, and as time goes on, the concentration of pheromones accumulated on shorter paths increases gradually, and the number of ants choosing this path is increasing. Finally, all ants will concentrate on the optimal path under the action of positive feedback, which corresponds to the optimal solution of the problem to be optimized. We regard location ① as nest and location ② as a food source.

Ants are randomly placed in the nest. Ant *k* travels from grid *i* to grid *j* according to a certain probability. Its probability is determined by the following three points.

(1) Accessible List

The table is used to store the grid that the *k-th* ant has not visited at the current time *t*. Before selecting the next grid, each ant retrieves the table to determine whether the next grid to be visited has been visited or not, so as to avoid repeated visits.

(2) Expectation level

The expectation level is defined as the reciprocal of distance, which can be described as follows:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \tag{8}$$

In Eq. 8, d_{ij} represents the distance from *i* to *j*, and the shorter the distance, the greater the expectation level of ants from grid *i* to grid *j*, from which the ant guides the search.

(3) Pheromones

When ant *k* selects grid *j* from grid *i*, it will leave a pheromone $\tau_{ij}(t)$ on the road of *i-j*. The update of pheromones is reflected in the increase of pheromones and the volatilization of pheromones. The update formula is:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{9}$$

In Eq. 9, $\tau_{ij}(t+1)$ represents the pheromone concentration from grid *i* to grid *j* at the time of $t+1$. It is the pheromone left by the volatilization at the time of *t* and the pheromone smeared by all ants at the time of *t*. The volatilization coefficient $\rho \in (0{,}1)$, $\Delta\tau_{ij}(t)$ denotes the sum of pheromones released by all ants on the path from grid *i* to grid *j*, and may be expressed as the following equation:

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{10}$$

In the Eq. 10, $\Delta\tau_{ij}^{k}(t)$ represents the pheromone left by the *k-th* ant on the grid *i* to the grid *j*, m is the number of ants, and $\Delta\tau_{ij}^{k}(t)$ is given by Eq. 11.

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q/L^{k}(t), & \textit{if ij visted} \\ 0 \quad , & \textit{if not} \end{cases} \tag{11}$$

In the above equation, Q is the preset parameter, indicating the intensity of pheromone, and $L^{k}(t)$ represents the path length of all the grids that the *k-th* ant passes through after choosing the grids *j* at *t* time.

So, the ant *k* travels from grid *i* to grid *j* according to a certain probability, and its probability is:

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}(t)]^{\beta}}{\sum_{s \in allow_k} [\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}(t)]^{\beta}}, & s \in allow_k \\ 0, & s \notin allow_k \end{cases} \quad (12)$$

The pheromone is the key to the ant colony algorithm. The purpose of each iteration of the ant colony algorithm is to operate the pheromone. After the algorithm ends, the path with the largest pheromone is left. This path is the optimal solution. So, W&E condition fuel consumption model is added to influence the pheromone's change. At time *t*, the initialization of pheromone is related to the working condition. For any path from grid *i* to grid *j*, there are:

$$\tau_{ij}(t) = 1 - \mu_j(t) \quad (13)$$

$\mu_j(t)$ is the influence degree of grid *j* at time *t*, which is proportional to Y_m. Since Y_m has a threshold Y_{max}, $\mu_j(t)$ has an upper limit ϱ, that is, τ_{ij} has a lower limit. When τ_{ij} is less than the lower limit, it is expensive to pass through the grid *j*, so the working grid *j* is removed from the $allow_k$ set.

Since the W&E Condition Fuel Consumption Model Y_m is introduced, the probability $P_{ij}^{k}(t)$ of the ant traveling from grid *i* to grid *j* should also be modified. The modified $P_{ij}^{k}(t)$ is:

$$\begin{cases} \arg\max\{\tau_{ij}(t)[\eta_{ij}(t)]^{\beta}\}, & s \in allow_k, \mu_j(t) \geq \varrho \\ \frac{[\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}(t)]^{\beta}}{\sum_{s \in allow_k} [\tau_{ij}(t)]^{\alpha} \times [\eta_{ij}(t)]^{\beta}}, & s \in allow_k, \mu_j(t) < \varrho \\ 0, & s \notin allow_k, \mu_j(t) < \varrho \end{cases} \quad (14)$$

5.2 The simulation experiment of the route design algorithm

To verify the effectiveness of the above algorithm, position (25.5, 40.5) as the starting point and position (24.5, 0.5) as the ending point are chosen. The parameters of α, β and ρ are set and they are iterated 300 times with 200 ants. The route planning of ant colony algorithm without adding W&E condition fuel consumption Model and the generated iterative convergence curve are shown in Figs. 6 and 7. In these figures we assume that the edge length of the grid is 10 km.

From Fig. 7, it can be seen that the minimum route length is still in a state of oscillation with the increase of iteration times, which indicates that the minimum route length has not been found yet. The related parameters in the algorithm are not ideal, as the number of ants and the number of iterations are still insufficient. This is normal and it is to be expected that ACO algorithm's performance of metaheuristics is very dependent on the parameters' values.

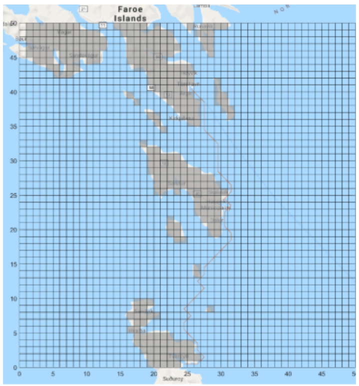

Fig. 6 Route planning

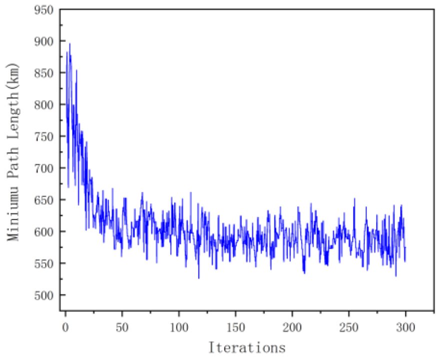

Fig.7 Shortest route iteration

This is the reason for which the computer scientists, that perform researches in this field, dedicate a lot of effort into determining appropriate values for them [18]. So, for optimal the algorithm's parameters values, we conducted multiple experiments, and the value of each parameter are selected as follows: The α optimal value is in the range of 1-2 and $\alpha = 1$ is selected; the β optimal value is in the range of 4-7 and $\beta = 7$ is selected; the ρ optimal value is in the range of 0.2-0.4 and $\rho = 0.3$ is selected. After parameter optimization, the ant colony algorithm planning route without adding W&E condition fuel consumption model is shown in Fig. 8, and the iterative convergence curve is shown in Fig. 9.

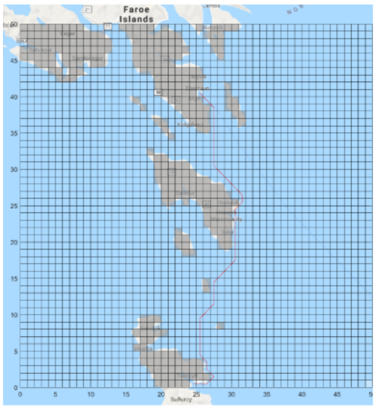

Fig. 8 Route planning with optimizing parameters

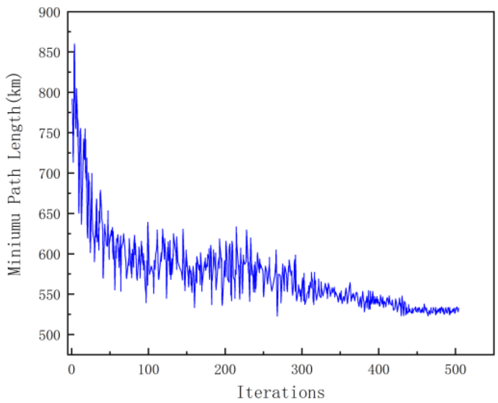

Fig. 9 Shortest route iteration with optimizing parameters

Then we conduct a comparison between the two shortest route iteration graphs. Although there is still an oscillation phenomenon exists in the iterative graph after optimization, the amplitude is obviously much smaller than the unoptimized one and basically remains below 55.

Furthermore, the W&E condition fuel consumption model is added to the ant colony algorithm, and the free grids are regarded as the W&E condition grids. When the ship reaches the W&E condition grids, the value of Y_m is calculated and compared with Y_{max}. If Y_m < Y_{max}, the ship can continue to sail in the W&E grids. If Y_m > Y_{max}, the ship needs to change route for energy saving. Then the modified ant colony algorithm is executed again, and the two different conditions are set to compare the three navigation routes. The result can be obtained as shown in Fig. 10.

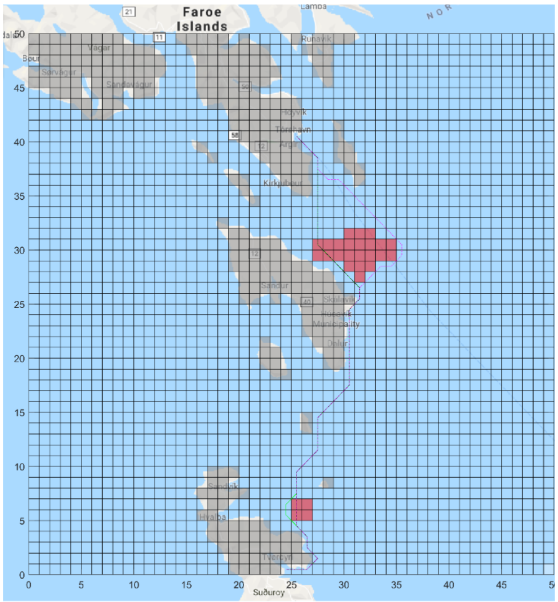

Fig. 10 Comparison of three navigation routes

The grids with red shadows in the Fig.10 represent the W&E condition grids, and the three routes are represented by three color lines respectively. Among them, green straight line is planned according to the modified ant colony algorithm with adding the W&E condition fuel consumption model; black dotted line is planned according to the original ant colony algorithm without considering the W&E condition grids; purple dotted line is planned according to the original ant colony algorithm that takes the W&E condition grids as obstacle grids.

According to the attributes of the W&E condition grids, when the ship reaches (25.5, 4.5), the working condition of the ship and environmental condition changes, which makes Y_m breakthrough the threshold value. Based on the principle of the modified ant colony algorithm, if the ship continues to follow the conventional route, the fuel consumption will increase sharply. If the ship sails along the green straight line, although the distance is increased, the total fuel consumption is reduced. When the ship sails to (31.5, 26.5), the working conditions of the ship and environmental condition have changed again. However, this change does not break through the threshold of Y_m, which means the fuel consumption value is within the acceptable range. If the ship sails in accordance with the purple dotted line, although bypassing the W&E barrier grids, ship fuel consumption value is higher than that of directly passing through the operating point.

6. Verification Based on Route Planning

To verify the correctness of the modified ant colony algorithm, we assume that the edge length of the grid is 10km. According to three routes mentioned above and fuel consumption data from the database of the ship *MS Smvril*, we calculate the average fuel consumption per kilometer of travel and draw a comparison chart as shown in Fig. 11.

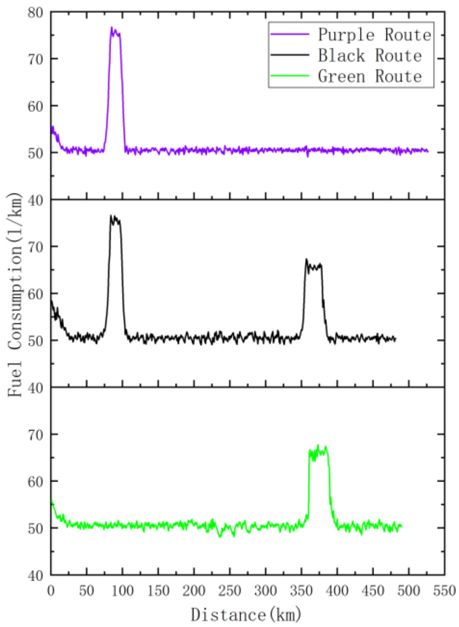

Fig. 11 Comparison of average fuel consumption of three navigation routes

It can be seen from Fig. 11 that when the sailed distance is about 77km, the average fuel consumption of the ship according to the black and purple lines will increase sharply because the ship just enters the first working and environment condition grid. When the distance is about 97km, the ship leaves the first W&E condition grid, and the average fuel consumption drops to the level of the grid without working and environment condition. When the sailed distance of the ship is about 353km, the average fuel consumption of the ship in accordance with the black line will increase, because the ship just enters the second W&E condition grid, and when sail away from the W&E grid, the average fuel consumption is restored to the average level; When the sailed distance of the ship is 361km, the average fuel consumption of the ship in accordance with the green line will increase, because the ship just enters the second W&E condition grid, and when sailing away from the W&E grid, the average fuel consumption is also restored to the average level.

On the base of average fuel consumption, the total fuel consumption of the three routes can be calculated and compared respectively as shown in Fig. 12.

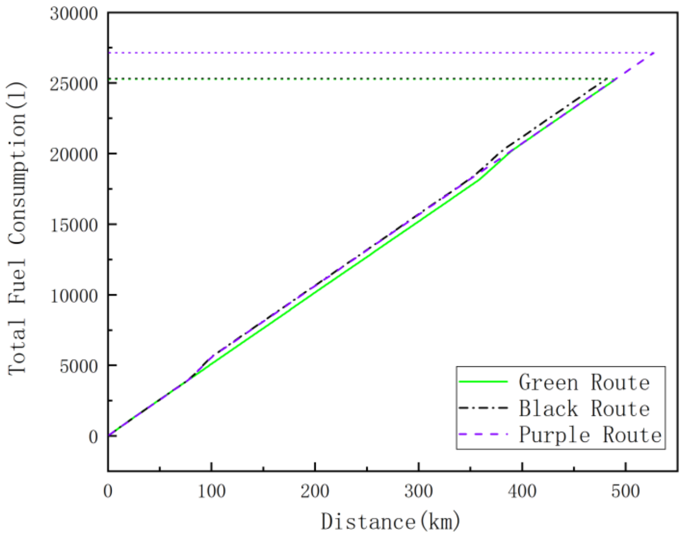

Fig. 12 Comparison of total fuel consumption of three navigation routes

It can be seen that the value of the vertical coordinates corresponding to the green line is the smallest. That is to say, the total fuel consumption of *MS Smyril* from position ① to position ② is the lowest, followed by black dotted lines and purple dashed lines. The result fully shows that the oil consumption of ships running along the green line is the lowest, and directly proves the correctness of the modified ant colony algorithm.

7. Conclusion

This paper studies the global ship trajectory optimization from the perspective of the shortest range, the lowest energy consumption, and safe obstacle avoidance. In order to obtain energy-saving navigation route of ship, the influential factors are selected to establish the dynamic fuel consumption model, then the ant colony algorithm is modified according to the fuel consumption model to achieve the optimal fuel consumption on the basis of the shortest route. It is concluded that the virtual grid model of sea with grid attributes of dynamic fuel consumption is efficient for route planning, and the navigation route planning by improved ant colony algorithm enables higher energy efficiency during ship operation.

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REFERENCES

[1] *M. Christiansen, K. Fagerholt, and D. Ronen*, "Ship Routing and Scheduling: Status and Perspectives", Transportation Science, **vol. 38**, 2004, pp. 1-18.

[2] *P. Andersson and P. Ivehammar*, "Cost benefit analysis of dynamic route planning at sea", Transportation Research Procedia, **vol. 14**, 2016, pp. 193-202.

[3] *Maria Catrina*, "RAILWAY STATION ROUTING ALGORITHM USING THE BACKTRACKING METHOD", University POLITEHNICA Bucharest, Series C: Electrical Engineering, **vol. 77**, no.4, 2015, pp. 335-346.

[4] *T. Lee and H. Nam*, "A Study on Green Shipping in Major Countries: In the View of Shipyards", Shipping Companies, Ports, and Policies. The Asian Journal of Shipping and Logistics, **vol. 33**, 2017, pp. 253-262.

[5] *P.G. Ayudhia and Semin*, "The Effect of Vessel Speed on Fuel Consumption and Exhaust Gas Emissions", American Journal of Engineering and Applied Sciences, **vol. 9**, 2016, pp. 1046-1053.

[6] *X.D. Meng and Z.X. Yuan*, "A minimum fuel consumption speed model considering effect of irregular wind and wave", Journal of Shanghai Maritime University, **vol. 37**, 2016, pp. 19-24.

[7] *N. Bialystocki and D. Konovessis*, "On the estimation of ship's fuel consumption and speed curve: A statistical approach", Journal of Ocean Engineering and Science, **vol. 1**, 2016, pp. 157-166.

[8] *Y.R. Shi and L.X. Dong*, "Ship Fuel Usage Monitoring System Based on Big Data Technology", 2nd International Conference on Intelligent Manufacturing and Materials, 2018, pp. 246-250.

[9] *George Anescu*, "A fast artificial bee colony algorithm variant for continuous global optimization problems", University POLITEHNICA Bucharest, Series C: Electrical Engineering, **vol. 79**, no.1, 2017, pp. 83-98.

[10] DTU Cognitive Systems Group. Propulsion Modeling. http://cogsys.imm.dtu.dk/propulsion modelling/ index.html, 2011.

[11] *R. Ye and J.S. Xu*, "Vessel Fuel Consumption Model Based on Neural Network", Ship Engineering, **vol. 38**, 2016, pp. 85-88.

[12] *J.P. Petersen, D.J. Jacobsen and O. Winther*, "Statistical modeling for ship propulsion efficiency", J Mar Sci Technol, **vol. 17**, 2012, pp. 30-39.

[13] *X.H. Mou, Y.P. Yuan, X.P. Yan and G.P. ZHAO*, "A Prediction Model of Fuel Consumption for Inland River Ships Based on Random Forest Regression", Journal of Transport Information and Safety, **vol. 35**, 2017, pp. 100-105.

[14] *A.L. Fan, X.P. Yan, Q.Z. Yin, X. Sun, Q.K. Chen and Y.B. Zhang*, "Energy efficiency model of marine main engine", Journal of Traffic and Transportation Engineering, **vol. 15**, 2015, pp. 69-76.

[15] G.Q. *Xia, Z.W. Han, B. Zhao, Y. Yang*, "Unmanned surface vessel path planning based on quantum ant colony algorithm", Journal of Harbin Engineering University, **vol. 40**, 2019, pp. 1-7.

[16] *Mccue L*. Handbook of Marine Craft Hydrodynamics and Motion Control [Bookshelf], IEEE control systems, **vol. 36**, 2016, pp. 78-79.
[17] *M. Dorigo and L. Maria*, "Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem", IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION, **vol. 1**, 1997, pp. 53-66.
[18] *Alina E. NEGULESCU*, "Normalization of Aco Algorithm Parameters", University POLITEHNICA Bucharest, Series C: Electrical Engineering, **vol. 79**, no.2, 2017, pp. 71-82.