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DOI
10.1016/j.apor.2021.102657

Publication date
2021

Document Version
Final published version

Published in
Applied Ocean Research

Applied Ocean Research 112 (2021) 102657

Contents lists available at ScienceDirect

Applied Ocean Research

journal homepage: www.elsevier.com/locate/apor

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ARTICLE INFO

Keywords:
Speed optimization
weather routing
energy consumption prediction
intelligent ship
low carbon shipping

ABSTRACT

It is of significant importance to optimize the energy consumption of ships in order to improve economy and reduce CO_2 emissions. However, the energy use of ships is affected by a series of navigational environmental parameters, which have certain spatial and temporal differences and variability. Therefore, the dynamic collaborative optimization method of sailing route and speed, which fully considers the spatial and temporal distribution characteristics of those factors, is of great importance. In this paper, the spatial and temporal distribution characteristics of the environmental factors and their related ship energy consumption profiles are first analyzed. Subsequently, a ship energy consumption model considering various environmental factors is established to realize the prediction of energy use of ships within the navigation region. Then, a novel dynamic collaborative optimization algorithm, which adopts the Model Predictive Control (MPC) strategy and swarm intelligence algorithm, is proposed, to further improve the ship's energy consumption optimization. Finally, a case study is conducted to demonstrate the effectiveness of the proposed method. The results show that the newly developed dynamic collaborative optimization method, which fully considers the continuously time-varying characteristics of environmental and operational parameters, could effectively reduce the energy consumption in comparison to the original operational mode. In addition, the adoption of the MPC strategy produces better performance results compared to the optimization method without the MPC strategy.

1. Introduction

As one of the world's most important modes of transportation, seaborne transport undertakes most of the world's trade (UNCTAD, 2019; Zheng et al., 2019). However, it causes a huge consumption of fossil fuels and serious carbon emissions (Perera and Mo, 2016; Psaraftis and Kontovas, 2014; Johnson et al., 2014). The International Maritime Organization (IMO) continuously introduces regulations and measures such as energy Efficiency Design Index (EEDI), Ship Energy Efficiency Management Plan (SEEMP) and Energy Efficiency Operation Index (EEOI) to conserve energy and reduce emissions in the shipping industry (MEPC, 2014). The improvement in the energy efficiency level of ships mainly depends on the optimization of fuel consumption for each voyage, and the sailing route and speed have a significant impact on this (Lützen et al., 2017; Yan et al., 2018). Therefore, the goal of reducing the total energy consumption during a voyage can be achieved by optimizing sailing parameters (speed, route), which can be promising methods of reducing carbon emissions and improving the shipping companies' profits (Konstantinos and Gerasimos, 2018; Poulsen and Johnson, 2016). In recent years, a great deal of research has been conducted in the areas of a ship's energy consumption modelling and prediction (Bialystocki and Konovessis, 2016; Tillig et al., 2018; Yang et al., 2019), sailing speed optimization (Li et al., 2020; Psaraftis and Kontovas, 2013; Chang and Wang, 2014; Adland et al., 2016) and route

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https://doi.org/10.1016/j.apor.2021.102657
Received 14 September 2020; Received in revised form 25 November 2020; Accepted 2 April 2021
Available online 31 May 2021
0141-1187/

optimization (Kim and Kim, 2017; Ma et al., 2020; Kim et al., 2020), and this has laid solid foundations for the energy savings and emission reductions of the shipping industry.

The energy use of ships can be affected by the navigation environment parameters including the wind, waves, and currents. These factors have large spatial and temporal differences and a complex variability, which lead to large variations in a ship's operating conditions and energy consumption levels under different navigational environments (Wang et al., 2018a). Therefore, research into the prediction and optimization of energy consumption should fully consider impacts of these environment parameters, and some work has been conducted in this area. For example, Yan et al. (2015) established a neural network model to evaluate the energy efficiency, based on data collected from ships, which could realize the prediction and evaluation of a ship's energy efficiency under different navigational environments. Furthermore, Meng et al. (2016) recommended a promising optimization model, which evaluate the parameters such as speed, displacement and environment through the log data, then further investigate the relationship between energy consumption and each factor. Lee et al. (2018) proposed a speed optimization model by analyzing the big data of navigational environments, which could reduce the energy consumption of ships effectively. However, these optimization methods only focused on the energy consumption optimization under a specific route, and did not consider the spatial and temporal differences of the navigational environment within a particular area to find a route that can contribute to a further reduction of the ship energy consumption to the minimum possible. Therefore, further research is demanded to optimize ships' energy use efficiency.

Some researchers have also considered a sailing route optimization method that takes into account the navigational environment, as this is also an effective way of reducing a ship's energy consumption (Vettor and Guedes Soares, 2016; Przemyslaw and Szlapczynska, 2018). For example, Shao et al. (2012) reported a meteorological alignment optimization method with dynamic programming. Their results showed that a 3% reduction in fuel use can be achieved by optimizing the ship's course and power simultaneously. Moreover, Sen et al. (2015) established a model using the shortest path method, then validated the model for route optimization. Zhang et al. (2018) proposed an automatic route optimization method, and ascertained that the automatic programming of a ship's optimal route could be realized by adopting a clustering algorithm and ant colony algorithm based on the data analysis. Zaccone et al. (2018) recommended a Three-Dimensional dynamic programming method for ship's voyage optimization aiming to select the optimal path and speed profile for a ship voyage on the basis of weather forecast maps. This method shows potential to improve the navigational safety and reduce a ship's energy consumption effectively. Wang et al. (2019) suggested using a Three-Dimensional Dijkstra's algorithm to achieve the planning of the ship's waypoints and sailing speeds along each waypoint, which led to at least a 5% reduction of fuel consumption within the cases analyzed. But this method can only be used in less severe marine environment. Gkerekos et al. (2020) presented a novel framework for vessel weather routing based on historical ship performance and current weather conditions, and a modified version of Dijkstra's algorithm that has been fitted with heuristics is applied recursively until an optimal route is obtained. However, this method only analyzed the optimization results at two fixed given sailing speed and did not fully consider the influence of various sailing speeds on the optimization results. Although the aforementioned researches achieved the joint optimization of the sailing rout and speed that considered navigational environment, these dynamic optimization algorithms do not fully consider the continuously time-varying characteristics and spatial and temporal differences of the environmental and operational information. Most of the existing weather routing methods rely on the prediction of the environmental information. However, as time goes by, the real-time actual environmental information may not be same as the predicted values at different time and space, thus influencing the optimization accuracy and robustness. Therefore, it is significant to consider the real-time updated environmental and operational information at each time step in a given time horizon, in order to improve the dynamic optimization performance of the sailing route and speed simultaneously.

In summary, the dynamic collaborative optimization method incorporating speed and route that considers the continuously time-varying navigational and operational conditions can be applied to further explore the potential energy consumption optimization. However, due to the large spatial and temporal differences and complex variability of navigational environment parameters, any study of this nature is more complicated. Thus, it is necessary to analyze the spatial and temporal distribution characteristics from the environmental parameters and energy consumption. In addition, to our best knowledge, there is no study that adopt the MPC strategy to achieve the dynamic collaborative optimization of sailing route and speed, in order to fully consider the continuously time-varying characteristics of environmental and operational information. MPC is an online-based optimization control technique which updates decision making variables in response to real-time information over a given horizon (Negenborn and Maestre, 2014). Compared to other methods, MPC has its obvious advantages including: i) the adoption of rolling optimization strategy to compensate for disturbances in time, thus improving the optimization accuracy and robustness; ii) its explicit way of handling constraints on actions, states and outputs; iii) suitability to systems with constraint, large delay and nonlinearity (Negenborn and Maestre, 2014). The main feature of MPC is the use of the rolling optimization strategy which can make up for the disturbances caused by uncertainties of the continuously varying parameters. Due to these advantages, it has been widely used in maritime transportation such as container handling and optimization control of waterborne AGVs (Xin et al., 2015; Zheng et al., 2016). MPC can also be used to deal with the dynamical collaborative optimization problem of sailing route and speed that considers the uncertainties and continuously time-varying characteristics of the environmental and operational conditions. This method can make up for the disturbances caused by the continuously time-varying environmental and operational information, thus helps to improve the optimization accuracy and robustness, so as to fully exploit the energy efficiency improvement potential.

This research is an extended version of previously reported papers (Wang et al., 2018a, 2020) and makes two main contributions: 1) the dynamic collaborative optimization model is established based on the analysis of the spatial and temporal distribution characteristics of the navigational environmental parameters and energy use. Both the interaction between route and speed and the spatial and temporal differences of multiple environmental factors are fully accounted for, in order to achieve a higher energy use optimization potential; and 2) a novel dynamic collaborative optimization method incorporating speed and route based on the MPC strategy and swarm intelligence algorithm is developed. This MPC-based joint dynamic optimization method fully considers the continuously time-varying characteristics of the environmental and operational information, and can achieve the dynamic collaborative optimization of the sailing route and speed under continuously time-varying environmental conditions, thus improving the optimization accuracy and robustness. The case study results show that the newly developed optimization method could effectively reduce the fuel consumption about 6.8% in comparison to the original operational mode. In addition, the adoption of the MPC strategy produces better performance results compared to the optimization method without the MPC strategy.

In this paper, Section 2 provides a brief analysis of the spatial and temporal distribution characteristics of the navigational environment parameters and energy use. Subsequently, predictive analytics of ship energy consumption is realized by establishing an energy use model that evaluates multiple influencing parameters in Section 3. Then, a dynamic collaborative optimization method incorporating speed and route is proposed in Section 4. On this basis, a case study has been carried out to verify the application of the model in Section 5. Finally, the conclusions

Table 1
Data acquisition form.

Item	Acquisition equipment	Installation position	Sketch
Navigation position	GPS instrument	Bridge	
Sailing speed	Speed log	Bridge	
Shaft speed and power	Shaft power sensor	Shaft	
Fuel consumption	Fuel consumption sensor	Fuel lines	

and suggestions for future work are presented in **Section 6**.

2. The spatial and temporal distribution characteristics of a ship voyage data

2.1. Data acquisition

In order to analyze the spatial and temporal distribution characteristics of the navigational environment and the related energy consumption, three types of the voyage data need to be collected: 1) The navigational data including the sailing speed and navigational trajectory; 2) The energy efficiency related data including the main engine speed, shaft power and fuel consumption; and 3) Navigational environment data, including wind speed and wind direction as well as wave height. The navigation speed is obtained by the odometer; the navigational trajectory is observed with a Global Positioning system (GPS); the shaft speed and shaft power are obtained by the shaft power sensor; and the ship energy use can be measured with a digital energy consumption sensor. For the acquisition of the meteorological environmental data, the data provided by the European Centre for Medium Range Weather

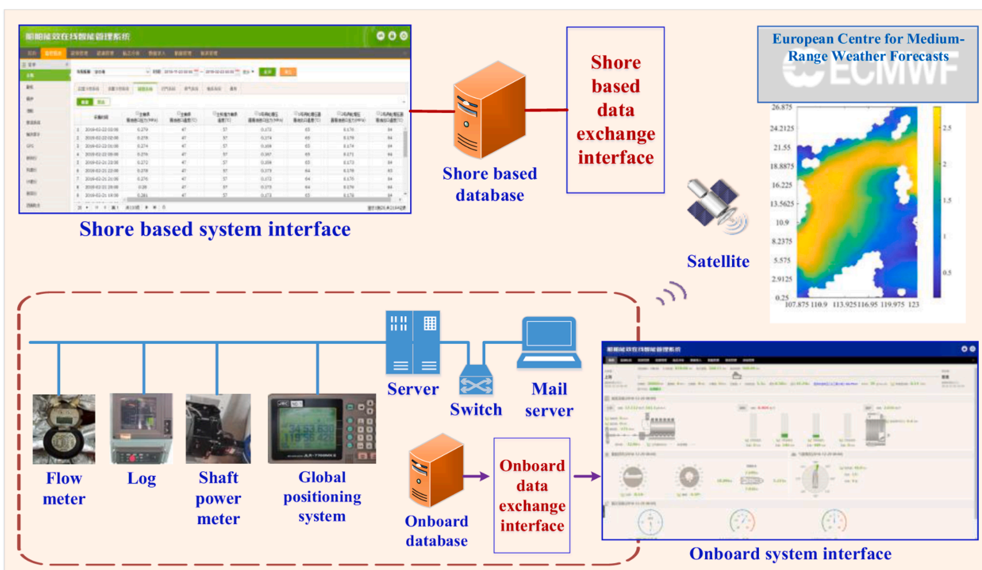


Fig. 1. A schematic diagram of the ship's energy efficiency data acquisition system.

Fig. 2. A schematic diagram of the target ship and navigational area.

Table 2
Some of the usable data obtained.

Date	Longitude value /(°)	Latitude value /(°)	Shaft power /(kW)	Sailing speed /(kn)	Energy consumption /(g/m)	Wind speed /(m/s)	Wind direction /(°)	Wave height /(m)
2015-12-28 10:00	108.4462 E	3.2261 N	10380	11.8	104.33	7.54	228.58	1.55
2015-12-28 10:10	108.4660 E	3.2541 N	10450	11.9	100.87	7.60	228.05	1.57
2015-12-28 10:20	108.4850 E	3.2806 N	10670	11.9	106.04	7.66	227.55	1.58
2015-12-28 10:30	108.5042 E	3.3068 N	10610	11.8	99.11	7.73	227.07	1.60
2015-12-28 10:40	108.5240 E	3.3346 N	10500	11.9	100.87	7.79	226.60	1.61
2015-12-28 10:50	108.5433 E	3.3608 N	10390	11.8	106.94	7.86	226.15	1.63
2015-12-28 11:00	108.5625 E	3.3870 N	10350	11.9	98.28	7.94	225.69	1.64
…	…	…	…	…	…	…	…	…

Forecasts (ECMWF) is used in this paper. The specific data acquisition details of the fuel efficiency related data and the installation position of the sensors used are summarized in Table 1.

The onboard energy efficiency data acquisition system developed is shown in Fig. 1. The obtained data is stored in the onboard data acquisition system, to be used for real-time display and auxiliary decision-making analysis. Meanwhile, the data acquisition system will package the collected data and send it to a shore-based data information platform, in order to provide the data for the analysis and decision-making by operators.

2.2. An analysis of the spatial and temporal distribution characteristics

The complex and time-varying navigational environment in different sections within the navigational area has different effects on a ship's sailing resistance and consequently its energy consumption. Therefore, it is necessary to analyze the distribution characteristics of the environment and energy consumption within the navigational area, in order to perform the sailing parameters optimization (route, speed) to reduce the energy use. In this paper, the spatial and temporal distribution characteristics of the environment and energy consumption within the navigational area are analyzed using the target ship "YU ZHONG HAI" and navigational area from Sunda Strait in Indonesia (0.25 ° N, 107.875 ° E) to Zhoushan in China (26.875 ° N, 123 ° E). The hydrographic and meteorological conditions of this navigational area are complex and thus it is an appropriate choice. The target ship and navigational area are shown in Fig. 2.

The target ship is equipped with the ship's energy efficiency data acquisition system mentioned above, which can obtain the required navigational data, energy efficiency related data, and navigational environment data. In order to ensure the accuracy of the wave height, wind speed and wind direction, the environmental information measured from the ECMWF (www.ecmwf.int), with the minimum grid interval (i.e. $0.125^\circ \times 0.125^\circ$), is used as the data source. The acquisition interval of the meteorological data is once every six hours, and thus the frequency is four times a day. In order to ensure the validity of the data, data preprocessing was done, which included: 1) Identification and reprocessing of abnormal data (Yin and Zhao, 2017); 2) Then, due to the inconsistency of the time interval and the location data in the collected meteorological data which is recorded by ships, the real time meteorological dynamic data in various positions and times of the navigational area are recorded by the 3D linear interpolation method. Some of the usable data obtained after the above steps are taken are shown in Table 2.

In addition, some of the spatial and temporal distribution characteristics of the environmental information, including wind speed and wave height, are shown in Figs. 3–4, while the spatial and temporal distribution of the energy efficiency for the original sailing route within the navigational area is shown in Fig. 5. As it can be seen from Figs. 3–4, the wind speed and the wave height at different sailing positions and different time periods have obvious differences. These differences in the navigational environments would influence the ship's energy

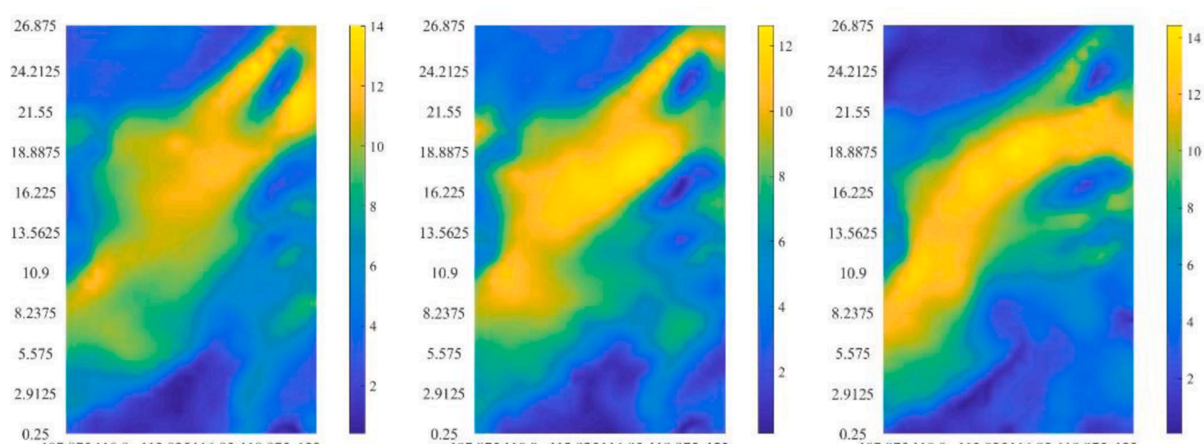
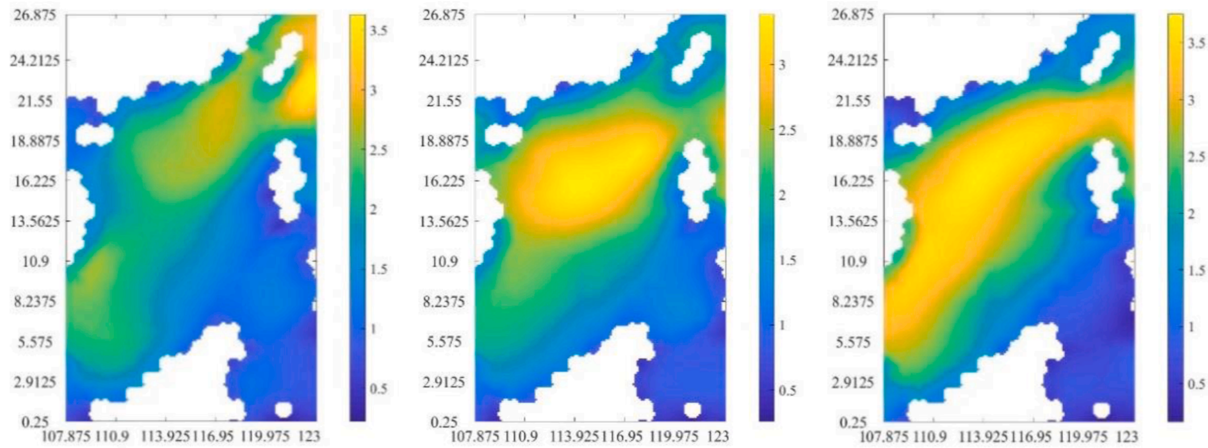


Fig. 3. Part of the spatial and temporal distribution characteristics of the wind speed.



(a) 2015.12.28 12:00 (b) 2015.12.30 12:00 (c) 2016.01.01 12:00

Fig. 4. Part of the spatial and temporal distribution characteristics of the wave height.

(a) Fuel consumption (t) (b) Sailing speed (kn) (c) Energy consumption (g/m)

Fig. 5. The spatial and temporal distribution characteristics of energy efficiency.

consumption. Therefore, the obvious spatial and temporal differences within the navigational environment lead to different energy consumption levels, as shown in Fig. 5. When the navigational environment becomes harsh, it will lead to an increase in the ship's resistance and subsequently increase the ship's energy consumption and vice versa. In addition, the ship's energy consumption is also related to the sailing speed. Therefore, it is a complex problem to achieve the dynamical collaborative optimization of the sailing route and speed. The key is to achieve the ship's energy consumption prediction under different sailing routes and speeds by taking full account of the spatial and temporal distribution characteristics of the navigational environment. On these bases, the MPC-based optimization algorithm can be adopted to achieve the dynamical collaborative optimization of the ship's energy consumption.

3. A Prediction of the ship energy consumption based on the distribution analysis

3.1. The ship energy use model considering various factors

A ship overcomes the resistance of water and air during sailing. To keep ship sailing at specific speed, main engine must provide a certain power to drive the propeller, in order to generate the thrust to push the ship forward. The effective thrust of the propeller should balance the hull resistance, as shown in Eqs. (1) and (2).

$$T_E = R = (1 - t)\cdot T \tag{1}$$

$$P_E = k\cdot R\cdot V_S \tag{2}$$

where T_E denotes the effective thrust of the propeller; R denotes the hull resistance; t denotes the thrust deduction fraction; T denotes the thrust from the main engine; P_E denotes the propeller's effective power; k denotes the number of propellers; and V_S denotes the sailing speed.

A ship sailing on the sea faces wind resistance above the waterline and water resistance below it. Water resistance is then divided into two parts: static and the added resistance attributed to the environment. The total resistance contains the static resistance, wave added resistance and wind resistance. Static resistance can be obtained by Eq. (3) (Holtrop and Mennen, 1982).

$$R_T = R_F(1 + k_1) + R_{APP} + R_W + R_B + R_{TR} + R_A \tag{3}$$

where R_T is the static resistance; R_F is the frictional resistance; R_{APP} is appendage resistance; R_W is the wave- making resistance; R_B is the bulbous bow additional resistance; R_{TR} is the stern immersion additional resistance; R_A is the relevant resistance; and k_1 is the viscous resistance factor from different ship types.

The wind resistance is calculated by Eq. (4) (Kwon, 2008).

$$R_{wind} = C_a \frac{1}{2} \rho_a {V_{wind}}^2 A_s \tag{4}$$

where C_a is the air coefficient resistance; ρ_a denotes the density of air; V_{wind} denotes the wind speed; and A_s denotes the positive projected area on the ship above the waterline.

The wave added resistance can be obtained through Eq. (5) (ITTC, 2005).

$$R_{wave} = 0.64 {\zeta_A}^2 B^2 C_b \rho g / L \tag{5}$$

where ζ_A denotes the characteristic wave height; B denotes the ship's breadth; C_b denotes the block coefficient; ρ denotes the density of the sea water; and L denotes the ship's length.

Finally, total resistance is obtained by Eq. (6).

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

where R_{wind} represents the wind resistance; R_{wave} represents wave added resistance.

The power output of main engine is transmitted to the propeller by the shaft and other devices. Due to various frictional losses, the power received by the propeller is less than that from the ship's main engine. After the propeller receives the power, it is converted into effective power to overcome the hull resistance through the interaction between the propeller and the hull. The relationships between the different kinds of power are shown as Eqs. (7) and (8).

$$P_B = P_D / (\eta_S \cdot \eta_G) \tag{7}$$

$$P_D = P_E / (\eta_O \cdot \eta_H \cdot \eta_R) \tag{8}$$

where P_B is the main engine power output; P_D is the power received by the propeller; P_E is the effective power to overcome the hull resistance; η_S is the shafting transmission efficiency; η_G is the gearbox efficiency; η_O is the propeller open water efficiency; η_R is the relative rotation efficiency; η_H is the hull efficiency; and w is the wake fraction.

In addition, the propeller thrust can be obtained by Eq. (9).

$$T = K_T \cdot \rho \cdot n^2 \cdot D^4 \tag{9}$$

where K_T is the thrust coefficient; ρ is the water density; n is the propeller speed; and D is the propeller diameter.

Then, the propeller advance coefficient and the open water efficiency can be obtained by Eqs. (10) and (11), respectively.

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

$$\eta_0 = \frac{K_T}{K_Q} \cdot \frac{J}{2\pi} \tag{11}$$

where J is the propeller advanced coefficient; V_A is the advanced speed; and K_Q is the torque coefficient.

From Eqs. (1), (9), and (10), the following relationship can be

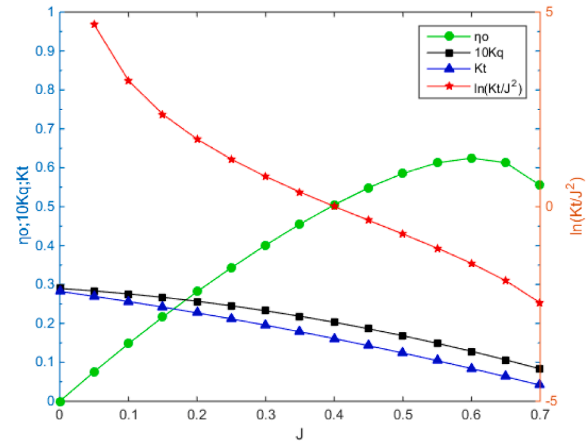


Fig. 6. The propeller open-water characteristic curve.

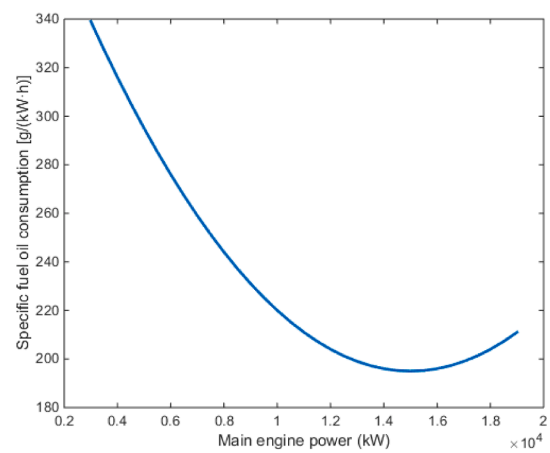


Fig. 7. The SFOC curve of the main engine.

ascertained.

$$\frac{K_T}{J^2} = \frac{R}{\rho \cdot (1 - t) \cdot (1 - w)^2 \cdot {V_S}^2 \cdot D^2} \tag{12}$$

The main engine output power is calculated by Eq. (13).

$$P_B = \frac{2\pi k \cdot \rho \cdot n^3 \cdot D^5 \cdot K_Q}{\eta_S \cdot \eta_G \cdot \eta_R} \tag{13}$$

According to Eq. (12) and the open water characteristic curve of the propeller in Fig. 6, the advanced coefficient of the propeller can be obtained, and then the corresponding torque coefficient can also be obtained from the open water characteristic curve of the propeller (Fan et al., 2016).

The Specific Fuel Oil Consumption (SFOC) of the main engine is closely related to the engine power. The characteristic curve of the SFOC is shown in Fig. 7, which illustrates the SFOC of the main diesel engine under different operational loads. Overall, the main engine energy use is calculated by Eq. (14).

$$q = \frac{k \cdot P_B \cdot g_{main}}{3600 \cdot V_s} \tag{14}$$

where q denotes the energy consumption per unit of distance travelled by the ship; and g_{main} is the SFOC of the main engine.

In summary, the modelling process of the ship's energy consumption is shown in Fig. 8, and includes the following steps.

(1) Calculate the ship's hull resistance according to the environmental factors and the ship's sailing speed;

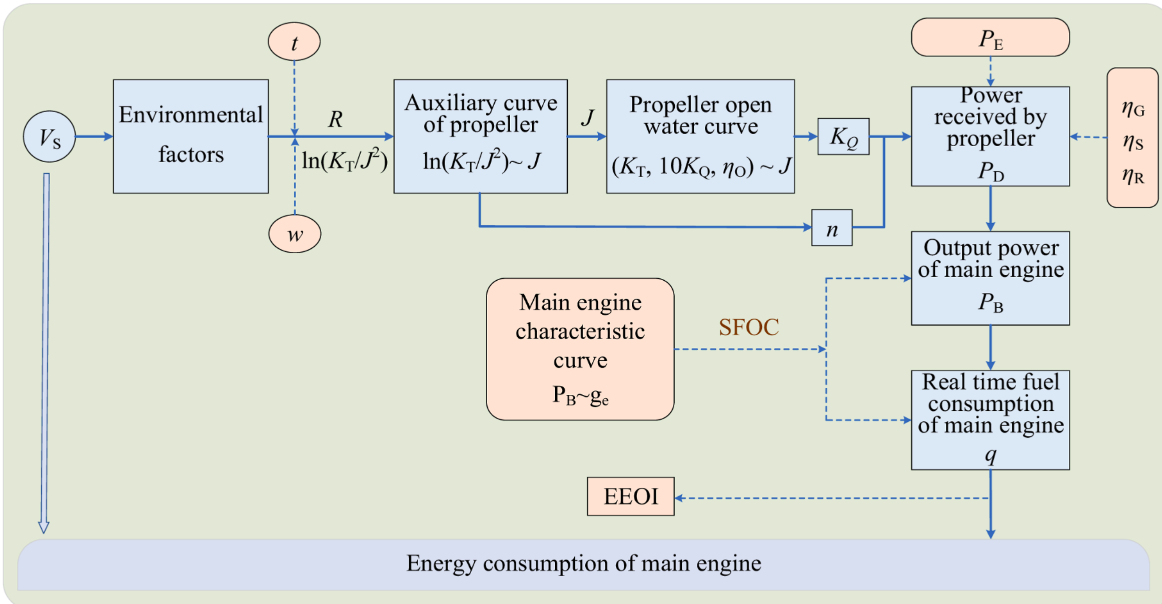


Fig. 8. The calculation processes for the ship's energy consumption.

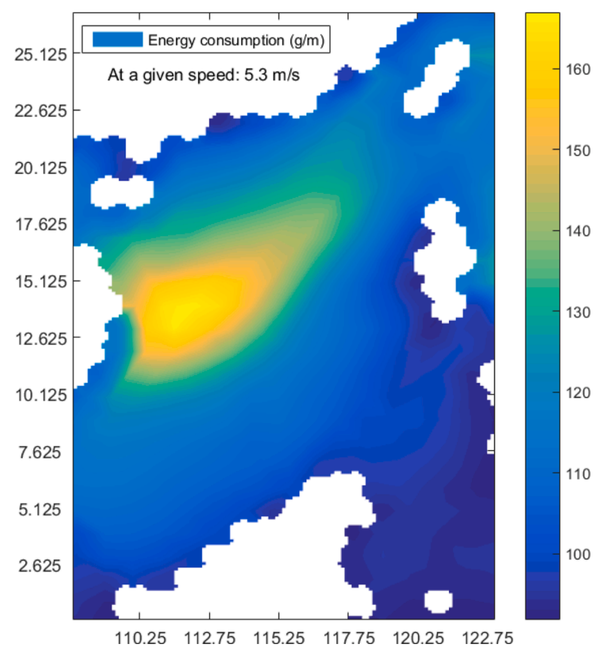


Fig. 9. The energy use prediction results for the navigational region.

(2) Then, obtain the propeller advanced coefficient through Eq. (12) and the open water characteristic curve in Fig. 6. Meanwhile, obtain the torque coefficient using a similar method through Eq. (12) and Fig. 6;

(3) Subsequently, obtain the corresponding propeller speed using Eq. (10);

(4) After that, obtain the main engine output power through Eq. (13), and the SFOC of the main engine by using the characteristic curve of main engine in Fig. 7;

(5) Finally, the main engine energy use is calculated by Eq. (14).

According to the ship energy use model established above, the fuel consumption of a ship per unit sailing distance changes with the ship resistance, which is mainly affected by voyage speed, wind speed, wind direction and wave height. Thus, to obtain the optimum energy use efficiency, it is crucial to reduce the ship's energy consumption by following an optimized route within the navigational area and using optimal sailing speed in each section of the route according to the environmental characteristics at different positions.

3.2. *The ship's energy use prediction within the navigational area*

Given the speed and specific navigational environment, the energy consumption within the navigational area can be analyzed and predicted, from traditional energy consumption method and the spatial and temporal distribution characteristics of the navigation conditions. The fuel consumption prediction results of the target ship within the navigational area under a specific speed (taking the sailing speed 5.3 m/s as an example) and the real-time navigational environment are provided in Fig. 9. As can be seen, the ship's energy consumption is different under different navigational conditions at different locations. The area with a milder environment is conducive for reducing energy consumption, thus reducing the ship's CO_2 emissions. However, the harsh environment in some sections will increase fuel consumption due to the high resistance of the ship, which will lead to higher CO_2 emissions. Therefore, determining the optimal route and sailing speed jointly within the navigation area is vital for achieving the optimization of the ship's energy use.

4. The dynamic collaborative optimization method incorporating speed and route

4.1. *The dynamic collaborative optimization*

The joint dynamic optimization in terms of sailing route and sailing speed not only evaluates both the interaction and influence between the two parameters, but also fully considers the time-varying dynamic characteristics of the navigational environment. The processes involved in the development of the joint dynamic optimization are depicted in Fig. 10.

The environmental information of the entire navigational area from port A to port B can be obtained before the ship's departure. The optimal sailing waypoints and speed between adjacent waypoints at different time steps is calculated by the reported energy consumption and optimization method. The ship will sail to the first determined navigational position $P^t(\mathrm{lat}^1, \mathrm{lon}^1)$, namely A_1, with the determined sailing speed $V(1, 1)$ at the first time step. When the navigational environment changes, the navigational environmental information within the navigational

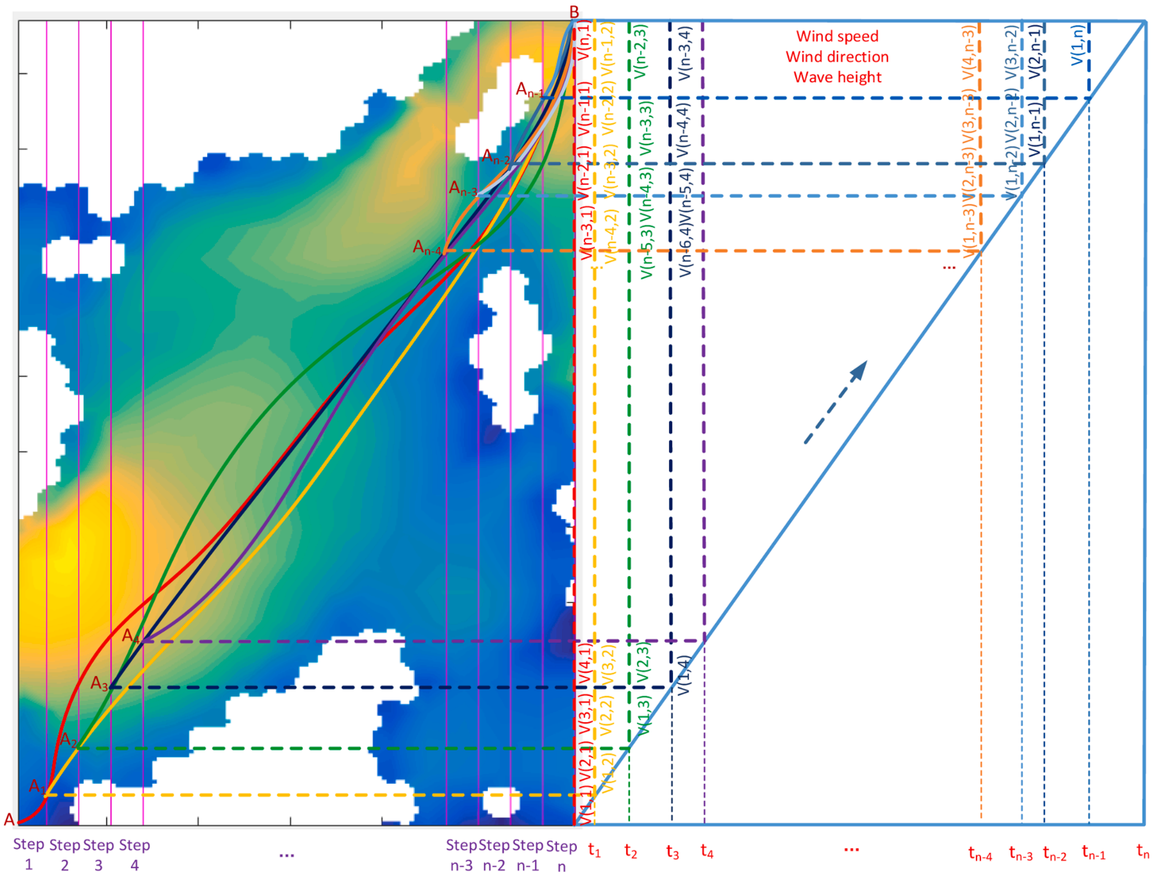


Fig. 10. A schematic diagram of the dynamic collaborative optimization processes.

area from position A_1 to port B should be respectively updated. When reaching $P^t(lat^1, lon^1)$, the newly determined optimization results from the updated navigational environmental information can be achieved again at the second time step. When the ship reaches A_1, it will move to the re-optimized position $P^t(lat^1, lon^1)$ with the re-determined sailing speed V (1, 2) as the second time step. Similarly, the continuous optimization at different time steps will continue until the ship arrive its target port B. This joint dynamic optimization fully considers time-varying information of navigation environment and ensures an optimized system for each step; which means that the ship sail at optimized route and speed at each time step, which reduces its energy use and emissions effectively in the route.

When the ship sails from port A to port B, the distance between every point is expressed as Eq. (15).

$$S^t = R\cdot 2\cdot asin\left(\sqrt{\left(sin(a^t/2)^2\right) + cos(x^{t-1}\cdot\pi/180)\cdot cos(x^t\cdot\pi/180)\cdot sin(b^t/2)^2}\right) \tag{15}$$

where S denotes the sailing distance of each segment; t denotes the time step; x denotes the latitude value; y denotes the longitude value; and R denotes the earth radius. a^t and b^t can be calculated by Eqs. (16) and (17), respectively.

$$a^t = x^{t-1}\cdot\pi/180 - x^t\cdot\pi/180 \tag{16}$$

$$b^t = y^{t-1}\cdot\pi/180 - y^t\cdot\pi/180 \tag{17}$$

The total energy use is calculated by Eq. (18).

$$Q_{total} = \sum_{t=0}^{M}(q^t\cdot S^t) \tag{18}$$

where Q_{total} represents the total energy use for the entire voyage; and q^t represents the energy use per unit distance between position $P^{t-1}(x, y)$ and $P^t(x, y)$ at the time step t, and is the function of the sailing speed V^t and the environmental factors between position $P^{t-1}(x, y)$ and $P^t(x, y)$.

Overall, the dynamic collaborative optimization incorporating the route and speed is a multi-dimensional nonlinear optimization strategy. The optimization target and its constraints are calculated in Eqs. (19)–(23).

$$\min \quad Q_{total} = \sum_{t=0}^{M}(q^t\cdot S^t) \tag{19}$$

$$P^M(x_i, y_i) = P\left(lat_{final}, lon_{final}\right) \tag{20}$$

$$T_{total} = \sum_{t=0}^{M}(S^t / V^t) \le T_{limit} \tag{21}$$

$$V_{\min} < V^t = S^t/T < V_{\max} \tag{22}$$

$$N_{\min} < N^t < N_{\max} \tag{23}$$

where T_{limit} is the sailing time constraint; T_{total} is the total sailing time periods for the entire voyage; M is the total time steps for the entire voyage; T is the time period for one time step; N_{min} and N_{max} are the minimum and maximum engine speed respectively; and V_{min} and V_{max} denote the minimum and maximum sailing speed respectively.

Eq. (19) describes the optimization objective function with the sailing waypoints in various steps as the optimization parameters. **Constraints (20) and (21)** ensures that the ship can arrive at the destination within the given time period. **Constraints (22)** and **(23)** are the physical limits related to the sailing and engine speeds, respectively, in order to

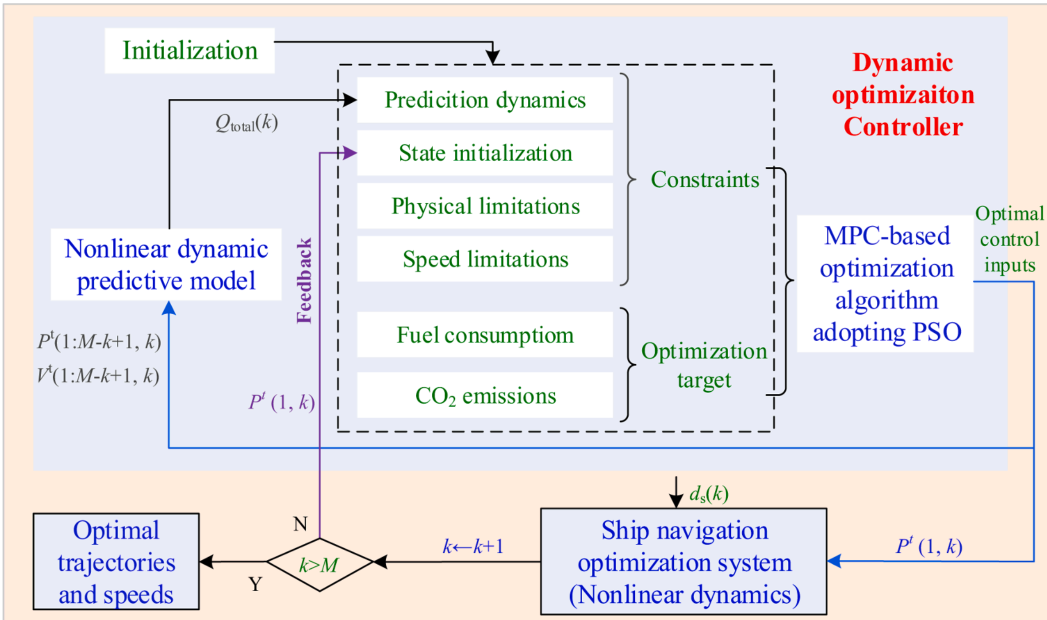


Fig. 11. A schematic diagram of the dynamic collaborative optimization controller.

prevent overloading.

For the proposed joint dynamic optimization problem of the sailing route and speed, the system's state information at time step t mainly includes the current position of the ship and the current environmental information, namely, the system disturbance, which is calculated by Eqs. (24) and (25). Then, at time step t, the state equation of the system can be expressed by Eq. (26).

$$Y_s(t) = P^t(x_i, y_i) \tag{24}$$

$$d_s(t) = \{V_{g,t}, V_{wind,t}, D_{wind,t}, H_t, P^t(x_i, y_i)\} \tag{25}$$

$$Y_s(t+1) = F_s(Y_s(t), u_s(t), d_s(t)) \tag{26}$$

where $Y_s(t)$ is the system state; t means the time step; $V_{g,t}$ is the sailing speed to the ground; $D_{wind,t}$ is the wind direction; H_t is the wave height; $P^t(x_i, y_i)$ is the sailing waypoint; $d_s(t)$ is the system disturbance; and $u_s(t)$ is the system input of the ship.

4.2. The dynamic optimization algorithm and controller design

(1) The dynamic optimization algorithm

Based on the model established above, a novel dynamical collaborative optimization of the sailing route and sailing speed is proposed, by adopting the MPC strategy and Particle Swarm Optimization (PSO), as shown in Algorithm 1. Solving the optimization problem using PSO algorithm mainly includes the following steps (Wang et al., 2018b).

Step 1): Initialize N_S particles having 2(M-k) dimensions (k means the k^{th} time step). The former M-k dimensions represent the latitude points at each time step, and the latter M-k dimensions represent the longitude points at each time step. The particles' fitness values are calculated by Eq. (18), and optimized values of individual particles and populations are determined by comparing the fitness values.

Step 2): Update the velocities and positions of these particles. The position of a particle varies with the velocity. The update of the velocity and position of the particle can be obtained through Eqs. (27) and (28).

$$\widetilde{V}^{\tau+1} = w\cdot\widetilde{V}^{\tau} + c_1\cdot r_1\cdot\left(\widetilde{p}_{best}{}^{\tau} - \widetilde{X}^{\tau}\right) + c_2\cdot r_2\cdot\left(\widetilde{g}_{best}{}^{\tau} - \widetilde{X}^{\tau}\right) \tag{27}$$

$$\widetilde{X}^{\tau+1} = \widetilde{X}^{\tau} + \widetilde{V}^{\tau+1} \tag{28}$$

where τ is the current iterating number; $\widetilde{p}_{best}$ represents the individual optimal value; $\widetilde{g}_{best}$ represents the global optimal value; $\widetilde{X}$ and $\widetilde{V}$ represents the particle's position and speed respectively; r_1 and r_2 are random numbers (between 0 and 1); c_1 and c_2 represent learning factors; and w is the inertia weight.

Step 3): Recalculate the fitness value of each particle that meets requirements of Eqs. (20)–(23), and update the optimal values of individual particles and populations.

Step 4): Iterate Step 2 and Step 3 until the algorithm meets the stopping criteria. Finally, all the optimal particles are obtained; that is, the optimal longitude and latitude points within the navigational area at each time step.

(2) The controller design for the energy use optimization

According to the above algorithm, the designed joint dynamic optimization controller for the sailing route and speed based on MPC strategy is shown in Fig. 11. The controller calculates the optimized solution once for each step, and then feeds the value back to the system, so that it can compensate for the optimization error caused by the continuously time-varying environment parameters. Through the designed controller, the dynamic collaborative optimization of sailing condition in terms of route and speed can be achieved, and the dynamic optimization of the ship energy use can be realized, thus ensuring the real time optimization of ship's energy use.

Table 3
The major factors of the ship "YU ZHONG HAI".

Item	Parameter	Item	Parameter
Length of the ship	327 m	Design speed	14.5 kn
Breadth of the ship	29 m	Number of blades	5
Width of the ship	55 m	Diameter of propeller	9.7 m
Deadweight	297959 t	Rated power of the engine	19000 kW
Draft of the ship	21.4 m	Rated speed of the engine	73 rpm

Table 4
The required parameters for PSO algorithm.

Parameters	c_1	c_2	w_{max}	w_{min}	$iter_{max}$
Values	2	2	0.9	0.4	100

5. Case study

5.1. Study case description

Based on the characteristics of navigation environment and energy efficiency distribution in the South China Sea, the validity of the proposed dynamic collaborative optimization model is verified by a case study. The case study takes aforementioned target ship “YU ZHONG HAI” and the navigation area from Sunda Strait to Zhoushan as the research objects. The major factors of the target ship are shown in Table 3.

5.2. The joint dynamic optimization results and analysis

For the joint dynamic optimization algorithm, the parameters required by the PSO method are given in Table 4. In addition, the time constraint is set as 179.67 hours based on the original operating data. The optimization results based on the above-established algorithm such as the optimized position and speed in each time step along the route are obtained.

The optimal sailing speed in each time step along the route are shown in Table 5. From the optimization results, the optimized routes and speeds are jointly calculated at each time step by the proposed joint dynamic optimization method. This dynamic collaborative optimization algorithm can optimize the sailing route and also the ship sailing speed at various segments during the whole trip simultaneously. Meanwhile, the spatial and temporal distribution characteristics of the navigational environment and energy efficiency are also examined by this method. This method can provide an automatic way to avoid extreme weather, which can cause a higher energy use, and thus reduce ships fuel consumption and CO_2 emissions.

As it can be seen from Table 5, the data in each row represents the optimized sailing speed at each time step. In addition, the optimization results of the sailing speed in the first row of Table 5, i.e., the optimization results at the first time step, denotes the optimization results without the MPC strategy. The optimization without the MPC strategy only executes the optimization results in the first time step. Therefore, the continuously time-varying conditions would result in a deviation of the optimization results and thus can not be used to obtain the optimal energy efficiency at every time step. Comparatively, the optimization results shown by the first entry in each row of Table 5, namely the first optimization results at each time step, denote the dynamic optimization results of the sailing speed with the adoption of the MPC strategy. The dynamic optimization results are obtained from real-time updated parameters for each time step, so as to improve the optimization accuracy and robustness, leading to a better energy efficiency. There are obvious differences among the optimization results of the different optimization methods, namely between the results in the first row and the first entry in each row in Table 5. This results from the deviation between the predicted and actual values of the navigational environmental factors.

To validate the dynamic collaborative optimization method, a comparative analysis including the energy consumption and emissions was performed. The original and optimal sailing routes for the joint optimization method without the MPC strategy, for the same trip, were

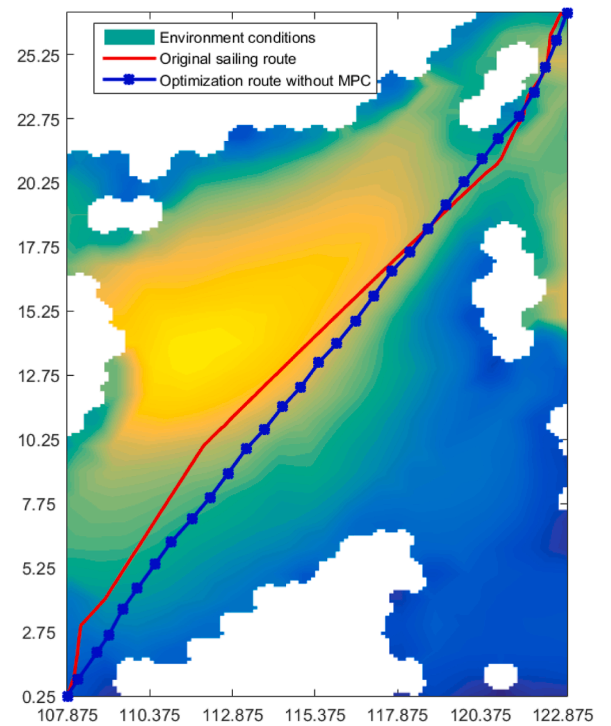


Fig. 12. The original sailing route and optimized sailing route without MPC strategy.

Table 5
The optimal sailing speeds at each time step along the sailing route (kn).

Time steps	The different sailing segments at each time step															
	1	2	3	4	5	6	7	8	9	10	……	23	24	25	26	27	28
1	**12.13**	**7.17**	**11.08**	**9.29**	**11.16**	**9.64**	**10.94**	**10.05**	**10.92**	**10.81**	**……**	**10.21**	**9.12**	**10.34**	**10.50**	**10.13**	**11.08**
2		**9.41**	11.16	10.92	9.89	9.29	9.80	10.24	9.60	9.84	……	11.24	11.57	9.62	10.94	10.75	10.92
3			**10.77**	10.56	9.41	10.83	11.29	9.49	9.91	11.12	……	10.21	8.73	9.84	10.94	10.42	11.08
4				**10.75**	9.56	9.84	10.59	10.40	10.63	10.07	……	10.87	10.67	9.87	10.50	10.50	11.08
5					**11.29**	11.27	10.71	8.24	10.22	10.77	……	9.62	10.75	9.70	10.59	10.38	11.04
6						**11.00**	10.07	10.26	9.80	9.91	……	10.17	10.17	10.42	10.44	10.42	10.96
7							**9.91**	10.63	9.78	9.84	……	10.22	10.40	9.95	10.44	10.50	11.24
8								**10.85**	10.44	9.86	……	10.22	10.42	10.13	10.38	10.44	11.12
9									**10.17**	10.28	……	10.75	9.93	9.84	10.63	10.21	11.08
10										**10.52**	……	10.61	9.29	10.22	10.42	10.19	11.12
……											**……**	……	……	……	……	……	……
23												**10.32**	9.23	9.84	10.50	10.52	11.25
24													**9.23**	9.82	10.63	10.21	11.31
25														**9.74**	10.50	10.36	11.33
26															**10.50**	10.36	11.33
27																**10.36**	11.41
28																	**11.49**

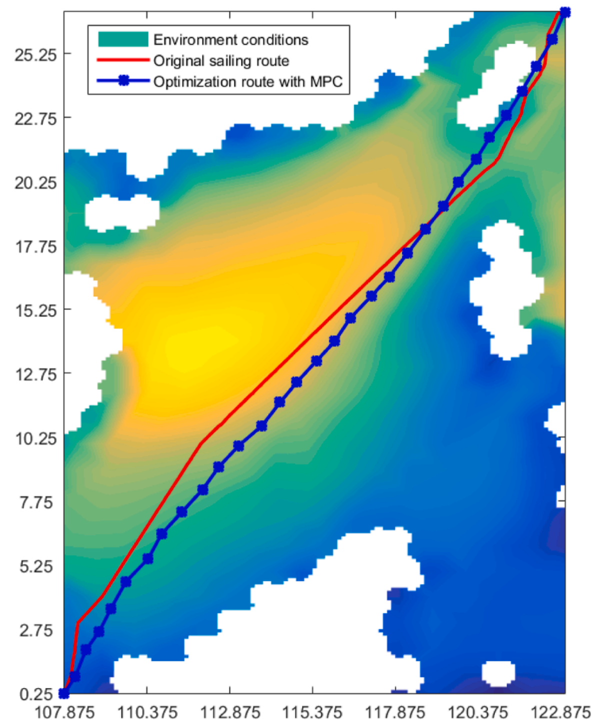


Fig. 13. The original sailing route and optimized sailing route with MPC strategy.

compared (Fig. 12). Additionally, the original and optimal sailing routes of the MPC-based joint dynamic optimization model are summarized (Fig. 13). Furthermore, the total energy consumption and emissions using the original operational mode and different optimization methods are shown in Table 6.

The CO_2 emissions in Table 6 are calculated by multiplying the fuel consumption by its CO_2 conversion rate (the used Heavy Fuel Oil is 3.114) (Baumler et al., 2014). The sailing trip and speed in the original operational mode, which does not fully evaluate the impact of environmental parameters on the energy use, are therefore not the most energy efficient because of the severe environmental parameters. The joint sailing route and speed optimization method without the MPC strategy can decrease the use of fuel and emissions by about 6.4% in comparison to the original operational mode. However, this model could not obtain the optimal optimization results, because it does not consider the continuously time-varying characteristics of the navigational environment. Consequently, the proposed MPC-based joint dynamic optimization method exhibited better optimization results, with an optimized figure of about 6.82% compared to the original method. Besides, the MPC-based joint dynamic optimization method could also decrease energy use and CO_2 emissions more efficiently than the joint optimization method without the MPC strategy, because it fully considers the continuously time-varying environmental conditions. Despite the MPC-based optimization method showing a longer sailing distance, hence a higher average sailing speed compared to the original operational mode, better optimization results were still achieved due to the milder environmental factor associated with the determined route, which in turn contributed to a reduced sailing resistance, thus reducing the ship's energy consumption. Accordingly, about 28 tons reduction in fuel consumption, and 87 tons CO_2 emissions reduction could be realized for a single voyage, using this joint dynamic optimization model. Therefore, the use of this model could significantly enhance a shipping company's market competitiveness due to the operational expenses' reduction. It can also be noted that the energy use reduction, thus CO_2 emissions reduction, can be achieved for the original voyage with worse as well as more obvious time-varying environmental conditions at different time steps.

6. Conclusions and future work

There is an urgent need to meet the energy saving and emission reduction requirements of the shipping industry. An effective way of improving the energy use efficiency of ships is the application of the joint dynamic optimization whilst considering multiple time-varying environmental factors. To fully exploit the potential of energy conservation and emission reduction from ships, a dynamic collaborative optimization model which evaluates a series of time-varying environment parameters is proposed. Based on the spatial and temporal distribution characteristics analysis of the navigation environment and the ship fuel efficiency, the predictive analytics for ships energy consumption is realized by the established energy consumption model. Based on this, a nonlinear dynamic model and control algorithm of the sailing parameters obtained from the MPC strategy and PSO algorithm is established. The case study demonstrates that this newly developed MPC-based joint dynamic optimization model can reduce the fuel use and CO_2 emissions by about 6.8% in comparison to the original navigational mode. Therefore, this method can save about 28 tons of fuel for a single voyage. It also greatly reduces the ship's operating expenses and improves the shipping company's competitiveness in the market. Furthermore, the MPC-based joint dynamic optimization method can also produce better optimization results than the joint optimization method without the MPC strategy under same navigational time constraints. Therefore, the method proposed in this paper has an important practical importance to promote efficient energy utilization and reduce emissions from the shipping industry.

The proposed dynamic collaborative optimization method in this paper is only based on the ship's navigational optimization, thus not limited to a particular type of ship. Therefore, it can also be applied to other types of ships. Furthermore, the joint dynamic optimization method in this paper that simultaneously considers multiple time-varying factors can be further extended to the joint dynamic optimization of an entire fleet. Therefore, the joint dynamic optimization of a

Algorithm 1
The dynamic collaborative optimization algorithm based on MPC strategy.

1. When the time step k=1, initialize the system state and system disturbance (including the navigational environment and initial navigational waypoint);
2. **While** $k \leq M$ **do**
3. When measuring the k time step, the current state $Y_s(k)$ and the disturbance $d_s(k)$ of the system are obtained by Eqs. (24) and (25);
4. Solve the Multi-dimension nonlinear optimization model in Eqs. (19)–(23) by adopting the PSO algorithm. The optimal solutions ($x_{k,} \dots, x_M, y_{k,} \dots, y_M$) at time step k are obtained as the system input $u_s(k)$;
5. The first step ($x_{k,}$ y_k) of the optimal solutions is carried out by using Eq. (26) to obtain a new system state $Y_s(k+1)$;
6. $k \leftarrow k+1$ and return to step 2;
7. **End while**

Table 6
Analysis of the energy use and emissions comparison.

Items	Total distance (km)	Average speed (kn)	Fuel consumption (t)	CO_2 emissions (t)	Optimized percent
Original operational mode	3442.5	10.35	410.80	1279.23	–
Joint optimization without MPC strategy	3385.2	10.17	384.39	1196.99	6.43%
Joint optimization with MPC strategy	3389.1	10.19	382.77	1191.95	6.82%

fleet of ships energy use, which is a more complex optimization decision-making problem, should be considered for future research. Moreover, the integrated management planning and control of a fleet's energy use could be realized by studying the joint dynamic optimization method whilst considering various time-varying influencing factors, so as to promote the environmentally-friendly development of the shipping industry.

CRediT authorship contribution statement

Kai Wang: Conceptualization, Methodology, Investigation, Software, Validation, Funding acquisition, Writing - review & editing. **Hao Xu:** Conceptualization, Investigation, Writing - original draft, Validation, Writing - review & editing. **Jiayuan Li:** Investigation, Writing - original draft, Validation, Visualization. **Lianzhong Huang:** Methodology, Validation, Supervision, Project administration. **Ranqi Ma:** Conceptualization, Investigation, Writing - review & editing. **Xiaoli Jiang:** Methodology, Investigation, Writing - review & editing. **Yupeng Yuan:** Conceptualization, Methodology, Writing - review & editing. **Ngome A. Mwero:** Conceptualization, Visualization, Writing - review & editing. **Peiting Sun:** Methodology, Investigation, Supervision. **Rudy R. Negenborn:** Conceptualization, Methodology, Supervision. **Xinping Yan:** Conceptualization, Methodology, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors are grateful to the support of the National Natural Science Foundation of China (51909020, 52071045), the Project Funded by China Postdoctoral Science Foundation (2020M670735), the Natural Science Foundation of Liaoning Province (2019-BS-023), the Fund of National Engineering Research Center for Water Transport Safety (No. A2020001), the Project from Key Lab. of Marine Power Engineering and Tech. authorized by MOT (KLMPET2020-06), the Fundamental Research Funds for the Central Universities (3132020185, 3132019316). The authors are also thankful to the anonymous reviewers for their valuable comments and suggestions that significantly improved the quality of this paper.

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