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DOI
10.1016/j.trd.2018.04.005

Publication date
2018

Document Version
Final published version

Published in
Transportation Research Part D: Transport and Environment

Transportation Research Part D 62 (2018) 685–698

Contents lists available at ScienceDirect

Transportation Research Part D

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

Dynamic optimization of ship energy efficiency considering time-varying environmental factors

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ARTICLE INFO

Keywords:
Ship energy efficiency
Speed optimization
Dynamic optimization
Model predictive control
Energy conservation and emission reduction

ABSTRACT

Nowadays, optimization of ship energy efficiency attracts increasing attention in order to meet the requirement for energy conservation and emission reduction. Ship operation energy efficiency is significantly influenced by environmental factors such as wind speed and direction, water speed and depth. Owing to inherent time-variety and uncertainty associated with these various factors, it is very difficult to determine optimal sailing speeds accurately for different legs of the whole route using traditional static optimization methods, especially when the weather conditions change frequently over the length of a ship route. Therefore, in this paper, a novel dynamic optimization method adopting the model predictive control (MPC) strategy is proposed to optimize ship energy efficiency accounting for these time-varying environmental factors. Firstly, the dynamic optimization model of ship energy efficiency considering time-varying environmental factors and the nonlinear system model of ship energy efficiency are established. On this basis, the control algorithm and controller for the dynamic optimization of ship energy efficiency (DOSEE) are designed. Finally, a case study is carried out to demonstrate the validity of this optimization method. The results indicate that the optimal sailing speeds at different time steps could be determined through the dynamic optimization method. This method can improve ship energy efficiency and reduce CO_2 emissions effectively.

1. Introduction

Waterway transportation plays a key role in the international trade. The total trade volume of world seaborne shipments is more than 10 billion tons making over 80% of the total world merchandise trade in 2015 (UNCTAD/RMT). However, the induced problems including high energy consumption and serious environmental pollution could not be neglected. Accounting for more than 60% of the total operational costs, ship fuel expenses lead to a huge impact on the competitiveness of shipping companies. On the other hand, according to the research by the International Maritime Organization (IMO), maritime transport emitted 938 million tons of CO_2 constituting 2.6% of the world's total emissions in 2012 and it will increase by 150–250% by 2050 if no further measures are taken (Marine Environment Protection Committee, 2014). Inland waterway transport also has this problem. Take the Yangtze River as an example, there are about 60,000 ships sailing on it, achieving 1.92 billion tons of cargo transportation in 2013 (Yan et al., 2011). The

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https://doi.org/10.1016/j.trd.2018.04.005

Available online 01 May 2018

consumed energy of this large number of ships results in up to 5.27 million tons of CO_2 emissions, which should arouse wide concern for the shipping industry (Yan et al., 2010).

According to the IMO regulation, energy efficiency operational indicator (EEOI), which expresses the operation efficiency in terms of CO_2 emissions per unit of transport work, is used for measuring ship energy efficiency, as expressed in the following equation (International Maritime Organization, 2010). In which, j represents fuel type; FC_j is the total fuel consumption on the voyage, C_{carbon} is the carbon content of the fuel j; m_{cargo} is the mass of transported cargo; Dis is the voyage distance. For a given voyage, the fuel type, cargo capacity and the sailing distance is relatively fixed. Therefore, one method to reduce EEOI is to cut down the fuel consumption of the ship during the whole voyage.

$$EEOI = \frac{\sum_j FC_j \times C_{carbon}}{m_{\text{cargo}} \times Dis} \tag{1}$$

In order to improve ship energy efficiency, IMO has proposed some relevant measures including technical and operational measures, such as new energy applications (Beşikçi et al., 2016), propulsion system optimization design (Zhao et al., 2016), ship navigation optimization (Wang et al., 2015b, c) etc. In the case of in-service ships, a lot of research on speed optimization has been performed in order to improve energy efficiency (Corbett et al., 2009; Chang and Wang, 2014; Chang and Chang, 2013; Psaraftis and Kontovas, 2013; Psaraftis and Kontovas, 2014; Magirou et al., 2015; Fagerholt et al., 2010). Norstad et al. (2011) suggested that taking variable speed into consideration can significantly improve profit. Lindstad et al. (2011) studied the impact of speed reduction on the CO_2 emissions and transportation cost, and concluded that the shipping industry has much potential to reduce CO_2 emissions. Ronen (2011) focused on the determination of the ship speed and the number of ships for a container line by establishing a cost model to reduce the operating cost of the route. Recently, research on the optimization of ship energy efficiency has paid more and more attention to the large influence of navigational environment on the ship fuel consumption (Wang et al., 2015a; Chen et al., 2013; Lu et al., 2015; Beşikçi et al., 2015). Meng et al. (2016) focused on modeling the relationship between the fuel consumption rate and its determinants, including sailing speed, displacement, and weather conditions by using the shipping log data. Wang and Meng (2012) found that the fuel consumption even under the same sailing speed is different because of the different weather conditions and sea conditions. Furthermore, they established a mixed-integer nonlinear programming model to determine the optimal sailing speed for container ships.

In general, these methods only study the speed optimization of sea-going ships from the perspective of maritime logistics. In contrast, few studies have been done on the speed optimization of inland river ships (Sun et al., 2013; Yan et al., 2015; Wang et al., 2017b). The complex navigational environment of the inland waterway makes it rather difficult to decide the best sailing speeds for the inland river ships. Sun et al. (2013) calculated and analyzed the EEOI of an inland river ship under different working conditions based on experimental data. They demonstrated the huge impact of sailing speed and environmental factors on the energy efficiency of inland river ships. Yan et al. (2015) conducted a sensitivity analysis about the effect of environmental factors on ship energy efficiency by adopting a neural network method. On this basis, Wang et al. (2017b) proposed a quasi-static optimization method of engine speed through route division based on the statistical analysis of big environmental data, which took a step forward in the optimization of ship energy efficiency considering various navigational environments.

The above-mentioned speed optimization methods considering navigational environment are based on the static/quasi-static information on weather conditions from the weather forecast. In fact, weather forecast becomes less accurate over a long period of time due to inherent time-variety and uncertainty associated with these environmental factors. These static/quasi-static optimization algorithms could not ensure the real-time optimal energy efficiency during the entire voyage, due to the continuously varying environment. Therefore, it is better to develop a dynamic optimization and control method to improve ship energy efficiency considering the real-time updated environmental information. MPC is an on-line optimization-based control technique which updates decision making in response to real-time information over a given horizon (Negenborn and Maestre, 2014). The main characteristic of MPC is to use the rolling optimization strategy and can compensate for the disturbance caused by uncertainties of continuously varying parameters. Due to this advantage, it already has wide applicability in maritime transportation such as energy-efficient container handling and control of waterborne AGVs (Xin et al., 2015; Zheng et al., 2017; Negenborn and Maestre, 2014; Zheng et al., 2016). Therefore, MPC can also be used to deal with the dynamic optimization problem of ship energy efficiency considering time-varying environmental factors in this paper. In addition, the particle swarm optimization (PSO) algorithm is used to solve the established dynamic optimization model to obtain the optimal sailing speed under the real-time environment because of its ability to explore the problem's search space with lower computational complexity, especially in cases of complicated and non-linear objective functions or constraints (Kornelakis, 2010). Compared with the genetic algorithm, PSO has the advantage of faster convergence and fewer control parameters, and it has been widely used in some optimization problems (Wang et al., 2016b; 2017a). Thus; we apply this method to determine the optimal sailing speeds under different environmental conditions.

The objective of this paper is to achieve the dynamic optimization of ship energy efficiency considering time-varying environmental factors. By the adoption of MPC strategy, the optimal sailing speeds at different time steps can be determined to compensate for the disturbance caused by changing environmental factors. The decision and control method can assist the operators to fully tap the potential of ship operation energy efficiency optimization. The contributions of this study are twofold. From the perspective of theory, we establish the ship energy efficiency model considering time-varying environmental factors, so that it can effectively describe the ship energy efficiency under time-varying weather conditions. From the practical perspective, we extend the static and/or quasi-static method to a dynamic optimization method based on real-time updated environmental information. We demonstrate

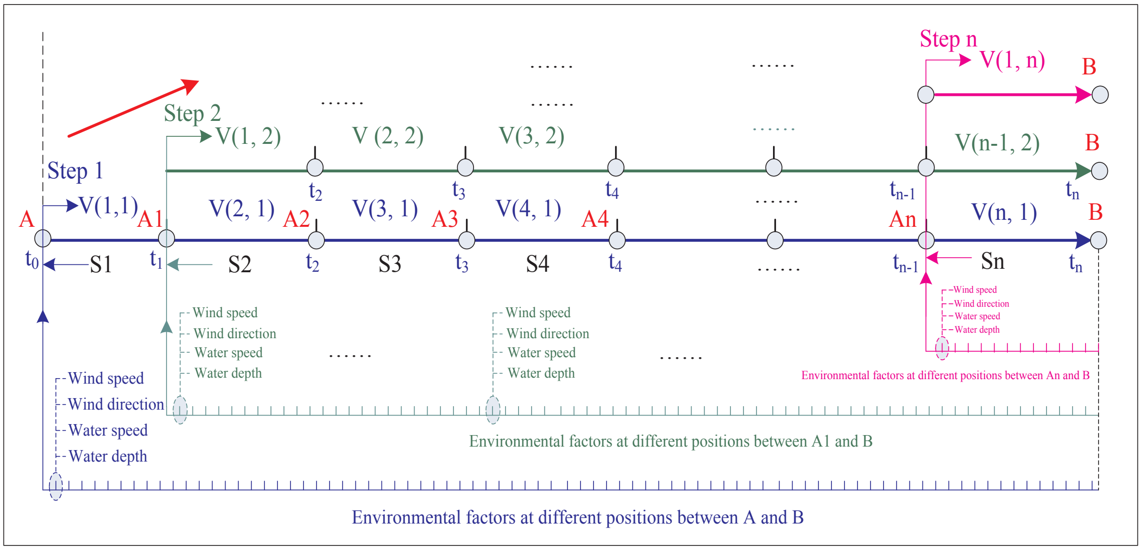


Fig. 1. Illustration of dynamic optimization problem.

that the developed algorithm and the designed controller can achieve the real-time optimized ship energy efficiency under the time-varying environment.

The remainder of this paper is organized as follows. Section 2 illustrates the problem and the method used in this paper. Then, the dynamic optimization model of ship energy efficiency considering time-varying environment is established and the MPC-based dynamic optimization algorithm and controller design are described in Section 3. Afterwards, a case study is conducted to demonstrate the effectiveness of the proposed dynamic optimization method in Section 4. Finally, conclusions and discussion are presented in Section 5.

2. Problem statement and method

2.1. Problem statement

During a voyage, the traditional static/quasi-static speed optimization methods are mainly based on the accurate forecasting weather information while not taking into account the continuously varying environment. These methods cannot ensure that the ship's energy efficiency is continuously optimal, especially when the navigational environment changes significantly and frequently over the length of the sailing route. Therefore, it is better to adopt the dynamic optimization method for the optimal speed determination considering the continuously varying environment, as shown in Fig. 1. A whole route can be divided into n legs with n time steps. At the first time step, by obtaining the navigational environment from the port A to the destination B, the optimal speed under the current environment at each leg can be determined through the established optimization model and algorithm. Then, the ship will be controlled sailing at the speed of $V(1,1)$, which is the determined optimal speed of the first leg at the time step 1.

With the time going on, the real-time updated navigational environment will be obtained again before arriving at position A1. Afterwards, by reapplying the established optimization model and algorithm, it is possible to determine the optimal speeds under the updated environmental conditions for the remaining n-1 legs. When the ship arrives at A1, it will be navigated at the re-optimized speed of $V(1,2)$ obtained at the second time step. In a similar way, continuous multiple optimizations would be conducted until the ship finally reaches the destination B. Therefore, the dynamic optimization method can compensate for the distortion of the optimization result caused by the change of the navigational environment over time. It can ensure the optimal solution of the system at each time step, that is, the ship can sail at the optimal speed at each time step.

2.2. Method

2.2.1. Model predictive control

MPC is an optimization-based control strategy, as shown in Fig. 2 (Zheng et al., 2017). Its current control action is obtained by solving a finite time-domain optimization problem at each time step, and only decision for the upcoming step will be implemented. Compared with other control algorithms, MPC has its own characteristics and obvious advantages including: (i) its explicit way of handling constraints on actions, states and outputs; (ii) adopt rolling optimization strategy to compensate disturbance in time, achieving better dynamic control performance; (iii) suitable for systems with constraint, large delay and nonlinearity (Negenborn and Maestre, 2014).

With these advantages, MPC has aroused wide applications in the field of ship control and energy management. Zheng et al.

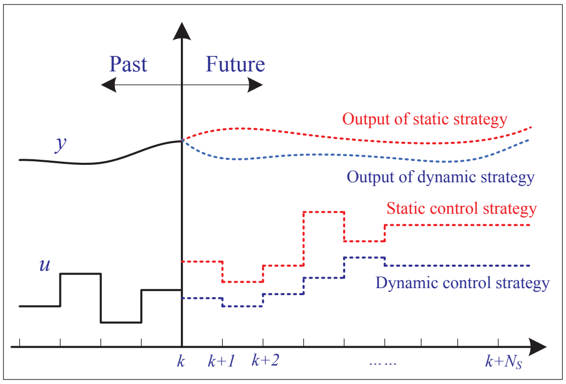


Fig. 2. Illustration of MPC (Zheng et al., 2017).

(2016) designed a predictive path following with arrival time awareness controller by adopting MPC strategy for Automated Guided Vehicles (AGVs). The controller can fulfill tasks successfully while meet system design criteria very well. Liu et al. (2015) achieved autonomous navigation control of underactuated vessels (USVs) considering environmental disturbances, by designing a trajectory tracking controller using Nonlinear Model Predictive Control (NMPC). In addition, Haseltalab et al. (2016) proposed to adopt MPC strategy for the combined motion control and energy management of hybrid ships, with the consideration of disturbance caused by surrounding environment. The simulation results show the effectiveness of the proposed method. Thus it can be seen, MPC is very suitable for the systems which have large disturbance and nonlinearity. Therefore, we propose to adopt MPC strategy for dynamic optimization of ship energy efficiency considering time-varying environmental factors.

2.2.2. Dynamic optimization process of ship energy efficiency

In this paper, the proposed dynamic optimization process of ship energy efficiency based on MPC strategy is shown in Fig. 3. It can be achieved through the following steps:

Step 1: Initialize and/or measure the state of the system at time step k;
Step 2: Establish the ship energy efficiency model considering time-varying environment factors;
Step 3: Formulate and solve the optimal sailing speeds in different legs under the related constraint at time step k;
Step 4: Establish ship navigation optimization system nonlinear model for improving energy efficiency and executive the first control input;
Step 5: $k \leftarrow k + 1$ and go to Step 1 until the optimization process is finished (when k > M, M is the total time step), then the optimal trajectories can be achieved.

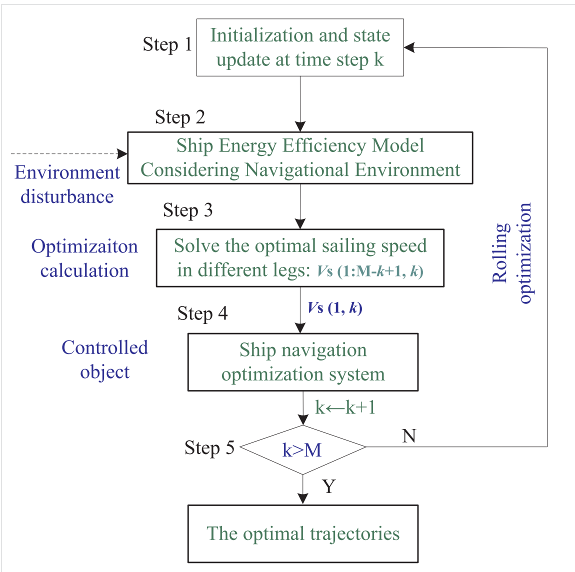


Fig. 3. Dynamic optimization process of ship energy efficiency.

Among others, the steps 2, 3, & 4 are critical in order to realize the dynamic optimization of ship energy efficiency considering time-varying environment factors. In this regard, they are illustrated in detail in the following section.

3. Dynamic optimization model and control method of ship energy efficiency

3.1. Dynamic optimization model of ship energy efficiency considering time-varying environmental factors

The energy consumption of a ship is mainly used to overcome the sailing resistance. After calculating the sailing resistance under different environmental conditions, the fuel consumption of the main engine can be obtained through the analysis of energy transmission among the ship hull and propeller as well as the main engine. The sailing resistance mainly includes the calm water resistance, wave adding resistance, wind resistance and shallow water resistance. After calculating these resistances using the method in (Holtrop and Mennen, 1982; Kwon, 2008; Townsin et al., 1975; Hu, 1986) respectively, the total resistance of the ship can be expressed by the following equation. It is a function of sailing speed, wind speed and direction, wave height, water speed and depth etc.

$$R_{ship} = R_T + R_{wave} + R_{wind} + R_{shallow} = F_R(V_s, V_w, V_{wind}, H, h) \tag{2}$$

where, R_T denotes the total hydrostatic resistance (N); R_{wave} denotes the wave adding resistance (N); R_{wind} denotes the wind resistance (N); $R_{shallow}$ represents the shallow water resistance (N); Vs denotes the ship sailing speed to water (m/s); V_w is the water speed (m/s); V_{wind}, H and h are wind speed (m/s), water depth (m) and wave height (m) respectively.

When the ship sails at a specific speed, The output power of the main engine can be calculated by the following equation (Wang et al., 2016a):

$$P_B = \frac{R_{ship} \cdot V_S}{k_0 \cdot \eta_S \eta_G \eta_O \eta_H \eta_R} \tag{3}$$

where, k_0 is the number of propellers; 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, $\eta_O = (K_T J)/(K_Q \cdot 2\pi)$, in which K_T is the thrust coefficient of propeller and K_Q is the torque coefficient, and J is the propeller advance coefficient; η_H is the hull efficiency, $\eta_H = (1-t)/(1-w)$, in which t is the thrust deduction coefficient and w is the wake coefficient.

Therefore, the output power of the main engine can be rewritten by the following equation:

$$P_B = \frac{R_{ship} \cdot V_S \cdot K_Q \cdot 2\pi \cdot (1-w)}{k_0 \cdot \eta_S \eta_G \eta_R \cdot K_T \cdot J \cdot (1-t)} \tag{4}$$

In which, the K_T and K_Q can be obtained by the interpolation polynomials method in (Bernitsas et al., 1981), which can be expressed as the following equations:

$$K_T = f_{K_T}(J);\ K_Q = f_{K_Q}(J) \tag{5}$$

When given the specific V_s and R_{ship}, we can get the specific value of J by the following equation:

$$\ln\left(\frac{K_T}{J^2}\right) = \ln\left(\frac{R_{ship}}{\rho(1-t)(1-w)^2 V_S^2 D^2}\right) = f(J) \tag{6}$$

where, ρ denotes the density of water (kg/m^3); D is diameter of the propeller (m).

Then, the energy consumption per unit distance of the main engines can be obtained by the following equation:

$$q_{main} = \frac{k_0 \cdot P_B \cdot g_{main}}{3600 \cdot V_g} = k_0 \cdot F_q(V_g, V_w, V_{wind}, H, h) \cdot g_{main} \tag{7}$$

where, q_{main} is the fuel consumption per unit distance of the main engines (g/m); V_g *is the* ship sailing speed to ground (m/s), $V_g = V_s \pm V_w$; g_{main} is the specific fuel consumption rate of the main engine (g/(kw h)).

As the main engines consume the most fuel, only the fuel consumption of the main engines is considered in this study. Therefore, the ship energy efficiency could be rewritten as the following equation.

$$EEOI = \frac{\sum_j FC_j \times C_{carbon}}{m_{cargo} \times D} = \frac{\sum_{k=1}^{M} (q_{main}(k) \cdot (V_g(k) \cdot \frac{T_{limit}}{M})) \times C_{carbon}}{m_{cargo} \times D} \tag{8}$$

where T_{limit} denotes the constraint of the sailing time (s); M means the total time steps of the whole voyage; $q_{main}(k)$ and $V_g(k)$ are the fuel consumption per unit distance (g/m) and sailing speed (m/s) of the k^{th} time step respectively.

Through the ship energy efficiency model considering time-varying environmental factors, the fuel consumption and sailing time corresponding to different sailing speeds under different environmental conditions can be calculated. For the navigation optimization system, it is a nonlinear optimization model. The optimization target and constraints of the optimization system can be expressed in the following equations.

$$\min EEOI = \sum_{k=1}^{M-k+1}\left(q_{main}(k)\cdot\left(V_g(k)\cdot\frac{T_{limit}}{M}\right)\right)\cdot\frac{C_{carbon}}{m_{cargo}\times D}\ ,\ \forall\ k\in\{1,2,\cdots\} \tag{9}$$

$$\sum_{k=1}^{M-k+1}\left(V_g(k)\cdot\frac{T_{limit}}{M}\right) = S_{total}\ ,\ \forall\ k\in\{1,2,\cdots\} \tag{10}$$

$$N_{\min} < f_{enginespeed}(V_g(k)\pm V_w(k)) < N_{\max}\ ,\ \forall\ k\in\{1,2,\cdots\} \tag{11}$$

$$V_{\min} < V_g(k)\pm V_w(k) < V_{\max}\ ,\ \forall\ k\in\{1,2,\cdots\} \tag{12}$$

where $V_w(k)$ are water speed (m/s) of the kth time step; S_{total} denotes the total distance of the whole route (m); $f_{\text{engine\_speed}}(V_g(k))$ is the engine speed of the kth time step (r/min).

Eq. (9) is the optimization objective function, in which the sailing speeds at different time steps are the optimization variables. Eq. (10) ensures that the ship can finish the whole voyage within the required time. Eqs. (11) and (12) are the physical limitations corresponding to the engine speed and the sailing speed respectively, which can avoid overloading.

3.2. Nonlinear system model of ship energy efficiency

The adoption of MPC strategy can predict the future response of the system based on the historical information of the controlled object, namely, the current state of the system and the current and future inputs as well as perturbations. For the problem of the dynamic optimization of ship energy efficiency in this paper, the current state information of the system mainly includes the current total sailing distance of the ship, and the current real-time updated environmental parameters (namely the disturbance of the system), which can be expressed by the following equations.

$$Y_s(k) = S_{total}(k) = \sum_{j=1}^{k} V_g(j)\cdot\frac{T_{limit}}{M}\ ,\ \forall\ k\in\{1,2,\cdots\} \tag{13}$$

$$d_s^{\tau}(k) = \{V_w^{\tau}(k), V_{wind}^{\tau}(k), H^{\tau}(k), h^{\tau}(k)\}\ ,\ \forall\ k\in\{1,2,\cdots\}\ ;\ \forall\ \tau\in\{k, k+1,\cdots\} \tag{14}$$

Then, the dynamics of the navigation optimizaiton at the time step k can be expressed as a state-space representation in the following equation:

$$Y_s(k+1) = F_s(Y_s(k), u_s(k), d_s^k(k)),\ \ \forall\ k\in\{1,2,\cdots\} \tag{15}$$

In which, the current input $u_s(k)$ of the MPC is obtained by solving a finite time-domain optimal control problem, namely the Eqs. (9-12). In this paper, the PSO algorithm, showing effectiveness in solving nonlinear optimization problem (Wang et al., 2016b; 2017a), is used to obtain the optimal solution of the nonlinear optimization problem of Eqs. (9-12) as the input of the system, according to the current system state. The solution processes are as follows:

Step 1: Initialize N particles with q ($q = 1, \ldots, M - k + 1$) dimensions at time step k and calculate the fitness values of these particles by using Eq. (9), and determine the individual optimal and group optimal value at time step k.
Step 2: Update the velocities and positions of these particles. The locations of the particles are changed according to their own velocity. The updates of velocity and location of each particle at each time step can be defined by:

$$\widetilde{V}_q^{\tau+1} = w\cdot\widetilde{V}_q^{\tau} + c_1\cdot r_1(\widetilde{p}_{best_q}^{\tau}-\widetilde{X}_q^{\tau}) + c_2\cdot r_2(\widetilde{g}_{best_q}^{\tau}-\widetilde{X}_q^{\tau})\ ,\ \forall\ \tau\in\{1,2,\cdots,\tau_{\max}-1\}\ ;\ \forall\ q\in\{1,2,\cdots,M\} \tag{16}$$

$$\widetilde{X}_q^{\tau+1} = \widetilde{X}_q^{\tau} + \widetilde{V}_q^{\tau+1}\ ,\ \forall\ \tau\in\{1,2,\cdots,\tau_{\max}-1\}\ ;\ \forall\ q\in\{1,2,\cdots,M\} \tag{17}$$

where τ is the current iterations times; $\widetilde{p}_{best}$ is the previous best; $\widetilde{g}_{best}$ is the global best; $\widetilde{X}$ is the particle's position; $\widetilde{V}$ is the particle's velocity; c_1 and c_2 denote the learning factors; r_1 and r_2 are the random numbers between 0 and 1; and w is the inertia weight.

Step 3: Recalculate fitness values of each particle which meets the constraints in Eqs. (10-12), then update the individual and population optimal value.
Step 4: Iterative Step 2 and Step 3 until the algorithm converges, then the optimal individual representing the optimal sailing speeds can be obtained as $(\widehat{V}_g(k),\ldots,\widehat{V}_g(M))$, which is also the input of the system $(\hat{u}_s(k),\ldots,\hat{u}_s(M))$ at the current time step k.

3.3. Controller design for the dynamic optimization of ship energy efficiency

Above all, the overall algorithm based on MPC strategy for the dynamic optimization of ship energy efficiency is summarized in the following algorithm.

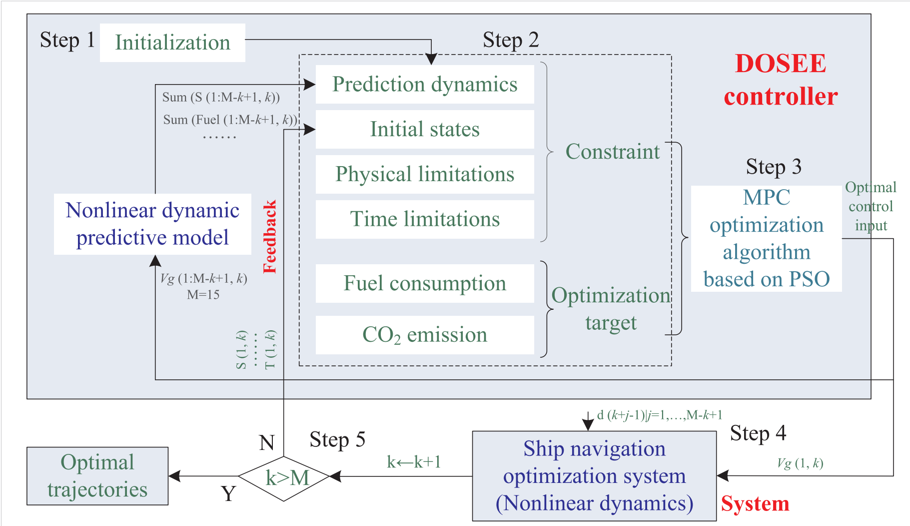


Fig. 4. Controller for dynamic optimization of ship energy efficiency.

Algorithm 1 Algorithm for the dynamic optimization of ship energy efficiency

1. Initialize the system state and environmental factors at time step k;
2. Measure the current state of the system $Y_s(k)$ and the environmental factors $d_s^{\tau}(k)$; $\forall\ k \in \{1,2,\cdots\}$; $\forall\ \tau \in \{k,k+1,\cdots\}$ at time step k;
3. Solve the nonlinear optimization model with the objective function in Eq. (9) and the constraints in Eqs. (10-12) based on the PSO algorithm, and obtain the optimal solution over the horizon: $(\widehat{V}_g(k),\ldots,\widehat{V}_g(M))$ as the planned input $(\hat{u}_s(k),\ldots,\hat{u}_s(M))$ of the system;
4. Only execute the first optimal decision $u_s(k)$ by using Eq. (15), resulting in the new system state $Y_s(k+1)$;
5. $k \leftarrow k+1$ and go to Step 2 until the optimization process is finished (when $k > M$, M is the total time step);

According to the above algorithm, we design a controller for dynamic optimization of ship energy efficiency (DOSEE), as showed in Fig. 4. The controller solves and obtains the optimal solution at each time step, and then inputs the first decision value to the nonlinear dynamic navigation optimization system. This DOSEE controller can compensate for the disturbence due to environmental changes at each time step. Through the design of this controller, the dynamic optimization of ship energy efficiency can be achieved, so as to ensure the real-time optimal ship energy efficiency.

4. Case study

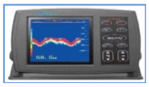
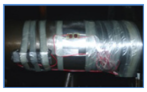
To validate the effectiveness of the proposed dynamic optimization method, we take a cruise ship and the waterway between Jiujiang and Shanghai along the Yangtze River (also called the lower reach of the Yangtze River) as a study case. The cruise ship and its parameters are shown in Fig. 5 and Table 1 respectively.

Fig. 5. Cruise ship on the Yangtze River.

Table 1
Parameters of the cruise ship.

Parameter	Value
Length of the ship	80 m
Width of the ship	14.8 m
Design sailing speed	28 km/h
Gross tonnage	4587 t
Design draft	2.7 m
Engine rated power	960 kW × 2
Engine rated speed	750 rpm
Propeller diameter	1.74 m

Table 2
Implementation form of the data acquisition.

Sensor	Remark	Sensor	Remark
	Wind speed sensor. To obtain the wind speed		Water depth sensor. To monitor water depth
	Water speed sensor. To monitor the water speed		GPS receiving device. To acquire sailing speed
	Shaft power tester. To collect speed and torque		Fuel consumption sensor. To gather fuel consumption

4.1. Data acquisition and analysis

(1) Data acquisition

The implementation form of the data acquisition is shown in Table 2. The wind speed and direction, water depth and speed were collected by the installed wind speed sensor, water depth and speed sensor. In addition, we also acquire the real-time sailing speed, shaft speed and torque as well the fuel consumption through the sensors of GPS, shaft power tester and fuel consumption sensor.

(2) Analysis of environmental factors and ship energy efficiency

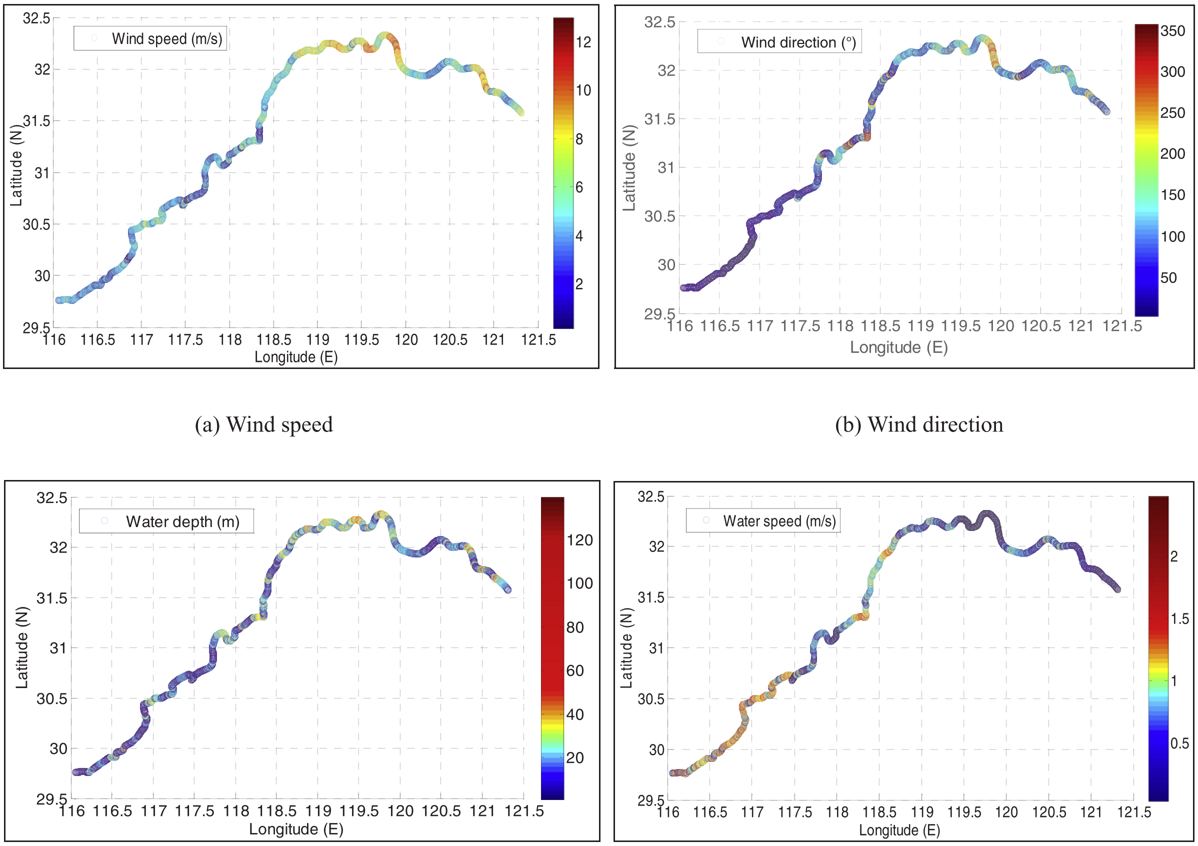
After collecting the data on environmental factors and ship energy efficiency, the data preprocessing ways, including removing the obvious abnormal data and interpolating the missing data, is conducted to obtain the final valid data. The navigational environment for different locations of the whole route is shown in Fig. 6 (a: wind speed; b: wind direction; c: water depth; d: water speed). As it can be seen, there are significant differences in the navigational environmental data at different locations. The large difference of navigational environment provides high potential for the optimization of ship energy efficiency because of the significant differences in the energy consumption under different navigational conditions.

The ship fuel consumption under different navigational conditions is the basis for the energy efficiency optimization. Therefore, the relationship among the navigational environment, sailing speed and the ship fuel consumption are analyzed, based on the established ship energy efficiency model considering time-varying environmental factors in this case study. The analysis results are shown in Fig. 7 (a: wind speed; b: wind direction; c: water depth; d: water speed). These results show that, the fuel consumption under different environmental factors and sailing speeds are largely different, which can support the idea that the ship energy efficiency can be improved by speed optimization under different environmental conditions.

4.2. Numerical experiment of the dynamic optimization method

From Shanghai to Jiujiang along the Yangtze River, we set the sailing time constraint is 60 h and the total time steps is 15, according to the changing magnitude and frequency of the weather conditions. In addition, according to the characteristics of the navigational environment, the Monte Carlo Simulation method (Fan et al., 2017) is adopted to generate the real-time updated navigational environment of the entire route. The purpose of the numerical experiment is to verify the effectiveness of the proposed dynamic optimization method.

By adopting the dynamic optimization algorithm proposed in this paper, the speed optimization results of different legs corresponding to different time steps are obtained, as shown in Table 3. The first row of the table corresponds to the results using the static optimization method, which does not take into account the changes in the navigational environment at each time step. The first



(a) Wind speed

(b) Wind direction

(c) Water depth

(d) Water speed

Fig. 6. Distribution of navigational environment data at different locations.

results in each row corresponds to the speed optimization results by adopting the dynamic optimization algorithm which consider the changes in the navigational environment, thereby ensuring that the ship operates at the optimal energy efficiency state at each time step. As it can be seen from Table 3, there exists a large difference between the results using static method (the values in the first row) and the results through the dynamic method (the first value in each row) at each time step. That is the reason why the ship energy efficiency could be optimized more effectively.

Based on the proposed dynamic optimization method, the obtained optimal results at different time steps, including fuel consumption and CO_2 emissions as well as EEOI per time step, are shown in Table 4. As it can be seen, the final fuel consumption and CO_2 emissions as well as EEOI are obviously different at different time steps, due to the large difference in the navigational environment. This is the main reason why we consider the dynamic navigational environment for the ship energy efficiency optimization.

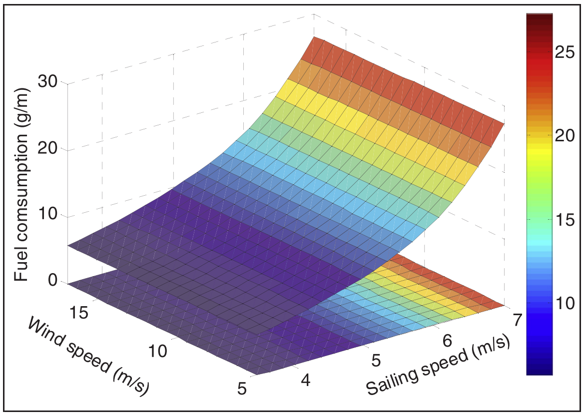
4.3. Analysis

4.3.1. Comparative analysis of different optimization methods

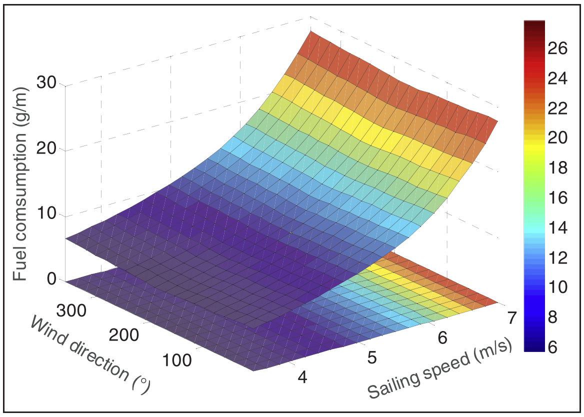
In order to identify the effectiveness of the proposed method, a comparative analysis is carried out. The results using static and dynamic optimization method, including fuel consumption and CO_2 emissions as well as EEOI at different time steps are shown in Fig. 8. As it can be seen, the optimization results are different because of the time-varying environmental factors.

In addition, Table 5 shows the total fuel consumption collected by the real ship and the corresponding CO_2 emissions as well as EEOI, and the total fuel consumption and CO_2 emissions as well as EEOI obtained by adopting the MPC-based dynamic optimization method and the static optimization method. It can be seen that the dynamic optimization method proposed in this paper can reduce fuel consumption and CO_2 emissions by about 28%, compared with the practical operation of the ship with lower sailing time (it mainly depends on the operator's experience, and the reduced percentage may be different for different operator, different sailing time or different legs under different weather conditions). It can also reduce fuel consumption and CO_2 emissions as well as EEOI by about 2%, compared with the static optimization method under the same situation. Therefore, the effectiveness of the proposed dynamic optimization method can be demonstrated.

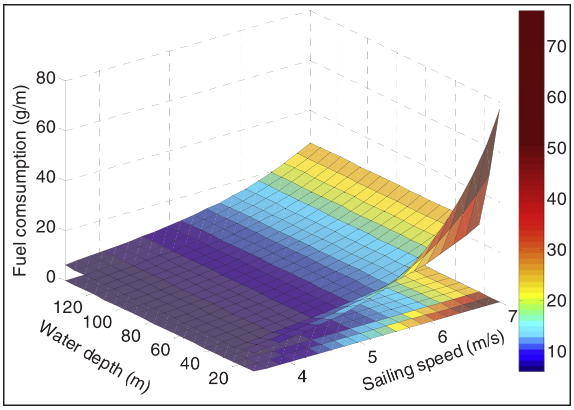
In order to further verify the effectiveness of the proposed method in this paper, we also use the quasi-static optimization method



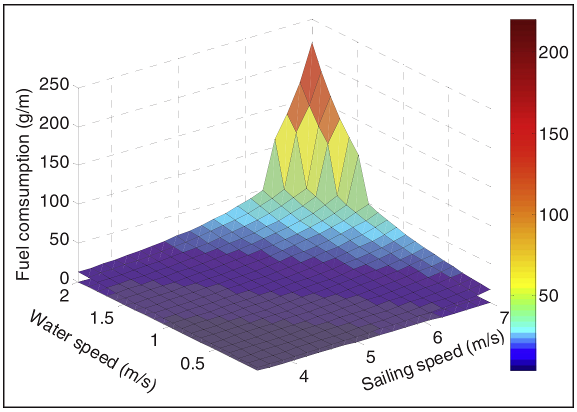
(a) Wind speed



(b) Wind direction



(c) Water depth



(d) Water speed

Fig. 7. Illustration of the relationship between environment and ship fuel consumption.

Table 3
Optimization results of sailing speeds (m/s) at different time steps.

Items	j = 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
k **= 1**	**4.7**	**4.5**	**4.0**	**4.6**	**4.5**	**4.2**	**4.3**	**4.2**	**4.4**	**4.6**	**3.9**	**4.3**	**3.5**	**3.8**	**3.6**
2		**4.1**	4.1	4.3	4.2	4.1	4.1	4.2	4.2	4.2	4.1	4.0	4.3	4.3	4.2
3			**4.2**	4.1	4.1	4.1	4.2	4.2	4.1	4.1	4.3	4.2	4.2	4.3	4.2
4				**4.2**	4.2	4.3	4.2	4.1	4.2	4.2	4.1	4.1	4.1	4.3	4.1
5					**4.2**	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.1	4.2	4.0
6						**4.2**	4.2	4.2	4.1	4.2	4.2	4.1	4.1	4.2	4.2
7							**4.2**	4.1	4.2	4.2	4.2	4.1	4.1	4.2	4.2
8								**4.2**	4.2	4.2	4.2	4.1	4.2	4.1	4.1
9									**4.2**	4.2	4.2	4.2	4.2	4.1	4.0
10										**4.1**	4.1	4.1	4.2	4.1	4.3
11											**4.1**	4.2	4.2	4.2	4.1
12												**4.3**	4.3	4.1	4.0
13													**4.0**	4.2	4.2
14														**4.3**	4.1
15															**4.1**

Note: T is 60 h; j is the divided sailing time steps within each T/15 h, named there are totally 15 legs; k is the optimization step.

Table 4
Optimization results at different time steps.

Time steps	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Fuel consumption(g/m)	7.12	8.85	9.02	8.83	8.71	8.84	8.43	8.64	8.48	8.04	8.01	8.68	7.76	8.41	7.77
CO_2 emissions (g/m)	22.82	28.37	28.91	28.32	27.93	28.35	27.02	27.7	27.18	25.76	25.67	27.83	24.89	26.97	24.91
EEOI per time step (g/t·n mile)	9.21	11.46	11.67	11.43	11.28	11.45	10.91	11.19	10.98	10.4	10.36	11.24	10.05	10.89	10.06

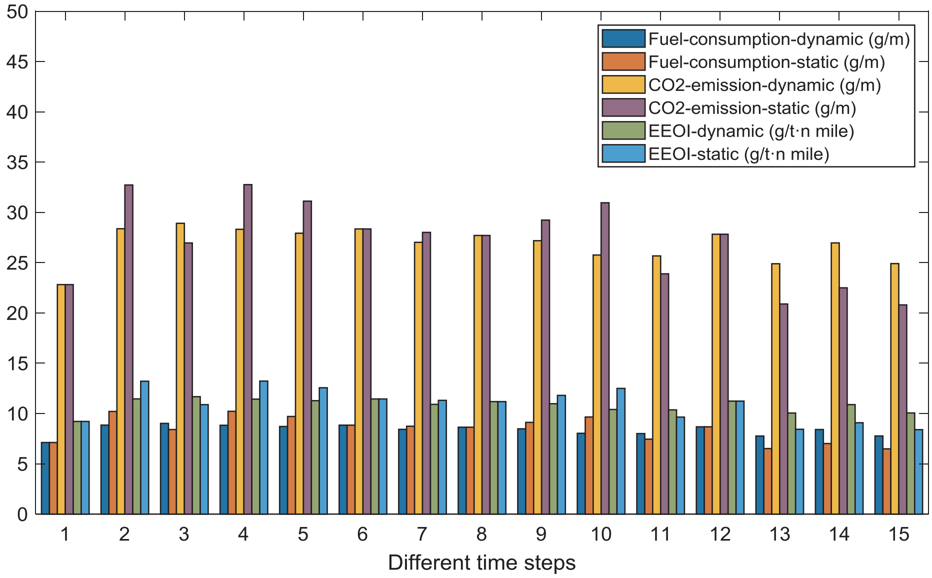


Fig. 8. Optimization results adopting static and dynamic optimization method.

Table 5
Comparison of the results adopting different methods.

Item	Dynamic optimization	Quasi-static optimization	Static optimization	Real ship data
Total fuel consumption (kg)	7602.32	7667.01	7754.11	10563.37
Total CO_2 emissions (kg)	24373.04	24580.43	24859.69	33866.16
EEOI (g/t·n mile)	10.83	10.93	11.05	15.05

proposed in reference (Wang et al., 2017b) for the same ship under the same conditions to optimize the energy efficiency. The quasi-static optimization method is based on the sailing route division through the statistical analysis of big environmental data. The optimization results including sailing speed, fuel consumption and CO_2 emissions as well as EEOI in each kind of divided sailing legs through this quasi-static optimization method are shown in Fig. 9. In addition, the total fuel consumption and CO_2 emissions as well as EEOI are given in Table 5. The results show that the ship energy efficiency in terms of EEOI and CO_2 emissions could be improved by only about 1% through this quasi-static optimization method comparing with the static method, while the ship energy efficiency could be improved by about 2% through the proposed dynamic optimization method in this paper. Thus it can be seen, a good improvement has been achieved by using the dynamic optimization method proposed in this paper.

4.3.2. Optimization result analysis considering the allowed time window

In order to verify the wide applicability of the proposed method, the speed optimization results under different sailing time constraints by using the proposed method are analyzed in this paper. The sailing time of the ship could be set as about 60 h. However, considering the influence of the weather condition, waiting time when calling ports and other influencing factors, it is common for the sailing time to have 2 h deviation to update within the overall scheduling. Therefore, we analyze the optimization result considering the allowed time window from 58 h to 62 h. The numerical analysis results are shown in Fig. 10. As it can be seen, the speed optimization results at each time steps decrease with the increase of the sailing time constraint, because larger time constraint provides more potential for the speed reduction and better ship energy efficiency. It is consistent with the theory of slow steaming for energy efficiency optimization.

In addition, Table 6 shows the total fuel consumption and total CO_2 emissions as well as EEOI under different time constraints. As it can be seen from the table, the dynamic optimization method shows better results than the static optimization method under different sailing time constraints. The reduced percentage of fuel consumption and CO_2 emissions as well as EEOI could be at least

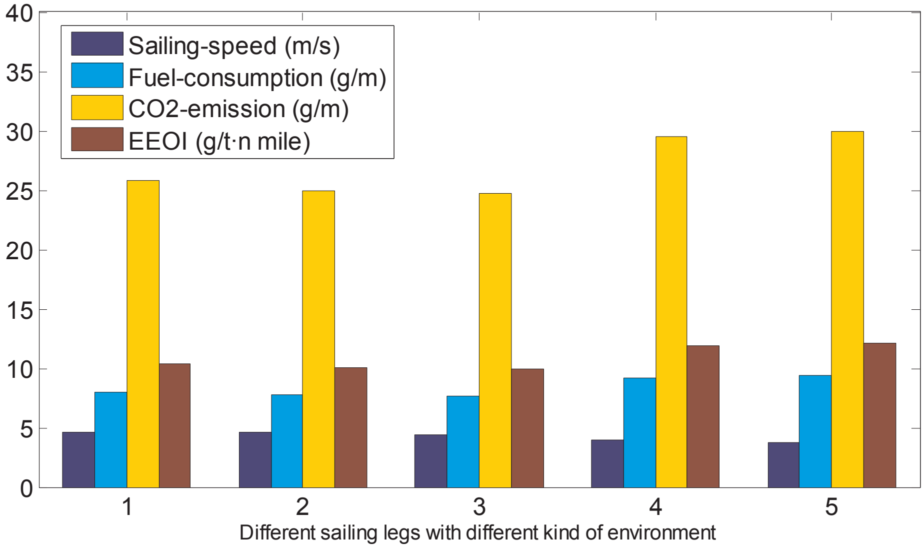


Fig. 9. Optimization results adopting the quasi-static optimization method.

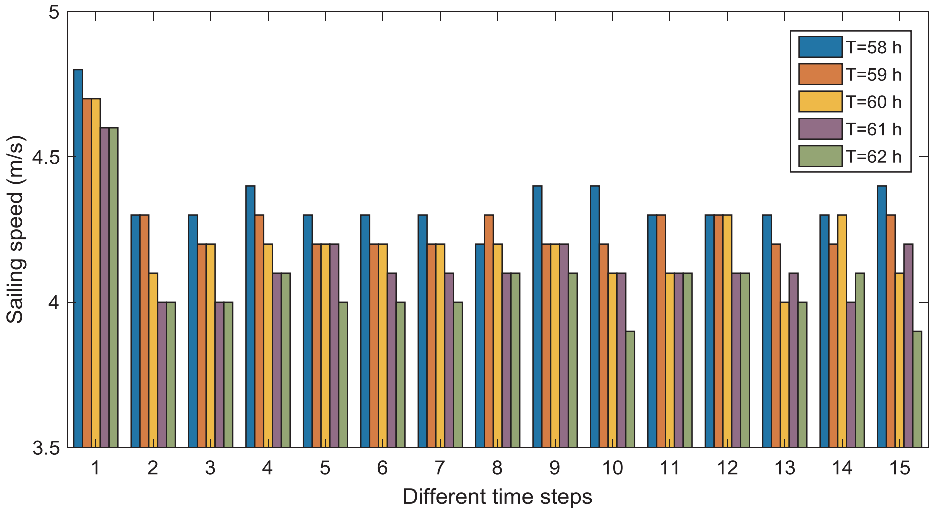


Fig. 10. Speed optimization results under different time constraints.

Table 6
Optimization results under different time constraints.

Items	58 h	59 h	60 h	61 h	62 h
Total fuel consumption by static optimization (kg)	8166	7931	7754	7544	7375
Total CO_2 emissions by static optimization (kg)	26,181	25,427	24,860	24,185	23,643
EEOI by static optimization (g/t·n mile)	11.65	11.31	11.05	10.76	10.52
Total fuel consumption by dynamic optimization (kg)	8015	7773	7602	7397	7222
Total CO_2 emissions by dynamic optimization (kg)	25,695	24,920	24,373	23,716	23,155
EEOI by dynamic optimization (g/t·n mile)	11.43	11.09	10.83	10.55	10.30
Reduced percentage (%)	1.86	2.00	1.96	1.94	2.07

1.86% when the time constraint is 58 h, and would be up to 2.07% when the time constraint is 62 h. Furthermore, with the increase of time constraints, the total fuel consumption and CO_2 emissions as well as EEOI by using both the MPC-based dynamic optimization method and the static optimization method show a significant downward trend. Therefore, we can conclude that improving the efficiency of entering and leaving port or the efficiency of loading and unloading can create more space for the improvement of the sailing time constraints, thus to improve the ship energy efficiency to a certain extent.

5. Conclusions and discussion

Considering the shortcomings of traditional static/quasi-static optimization methods, the dynamic optimization method of ship energy efficiency considering time-varying environmental factors is proposed in this paper. Based on the established ship energy efficiency model considering time-varying environmental factors and the nonlinear dynamic system model, the model predictive control (MPC) using the rolling optimization strategy is proposed to determine the optimal sailing speeds under the specific real-time updated environmental factors at different time steps. The designed DOSEE controller based on the optimization algorithm can compensate for the disturbance caused by changing environmental factors during the whole navigation. The case study illustrates the effectiveness of the proposed method, which can achieve the real-time better ship energy efficiency under the time-varying weather conditions. The optimization results show that the proposed method can improve ship energy efficiency more effectively than the static optimization method by about 2%. Also, it can reduce fuel consumption and CO_2 emissions by about 28% in ideal cases, compared with the practical operation of the ship. The amount of saved fuel per single voyage would be 2961 kg. It is a good benefit for the shipping company, especially in the era of recession of shipping industry.

The proposed optimization method can also be used for different kinds of ships, owing to the fact that it improves ship energy efficiency based purely on speed optimization. It should be noted that there exist more dynamic influencing factors, e.g., port operation, transport demand, and fleet deployment and management. Therefore, the dynamic energy efficiency optimization method of ship or even fleets, considering multiple dynamic influencing factors, would be the focus of future study. Due to the urgent requirement of energy saving and more and more stringent regulations on emissions, shipping companies bear huge responsibility on energy conservation and emission reduction. This paper proposes a new concept for optimizing ship energy efficiency through the dynamic optimization method. It provides the shipping companies a new way to reduce fuel consumption and CO_2 emissions.

Acknowledgements

This work is supported by National Key Technology Support Program (No. 2013BAG25B03), and the China Scholarship Council under Grant 201606950063 and the Hubei Provincial Leading High Talent Training Program Funded Project (File No. HBSTD [2012] 86).

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2018.04.005.

References

Bernitsas, M.M., Ray, D., Kinley, P., 1981. KT, KQ and efficiency curves for the Wageningen B-series propellers. Technical Report, University of Michigan.
Beşikçi, E.B., Arslan, O., Turan, O., Ölçer, A.I., 2015. An artificial neural network based decision support system for energy efficient ship operations. Comput. Operat. Res. 66 (C) 393–401.
Beşikçi, E.B., Kececi, T., Arslan, O., Turan, O., 2016. An application of fuzzy-AHP to ship operational energy efficiency measures. Ocean Eng. 121, 392–402.
Chang, C.C., Chang, C.H., 2013. Energy conservation for international dry bulk carriers via vessel speed reduction. Energy Policy 59 (1), 710–715.
Chang, C.C., Wang, C.M., 2014. Evaluating the effects of speed reduce for shipping costs and CO2 emission. Transport. Res. Part D: Transp. Environ. 31, 110–115.
Chen, C., Shiotani, S., Sasa, K., 2013. Numerical ship navigation based on weather and ocean simulation. Ocean Eng. 69 (9), 44–53.
Corbett, J.J., Wang, H., Winebrake, J.J., 2009. The effectiveness and costs of speed reductions on international shipping. Transp. Res. Part D: Transp. Environ. 14, 593–598.
Fagerholt, K., Laporte, G., Norstad, I., 2010. Reducing fuel emissions by optimizing speed on shipping routes. J. Operat. Res. Soc. 61, 523–529.
Fan, A., Yan, X., Yin, Q., 2017. Modeling and analysis of ship energy efficiency operational indicator based on the Monte Carlo method. Nav. Eng. J. 129 (1), 87–98.
Haseltalab, A., Negenborn, R.R., Lodewijks, G., 2016. Multi-level predictive control for energy management of hybrid ships in the presence of uncertainty and environmental disturbances. In: Proceedings of the 14th IFAC Symposium on Control in Transportation Systems (IFAC CTS 2016), Istanbul, Turkey, pp. 90–95.
Holtrop, J., Mennen, G.G.J., 1982. An approximate power prediction method. Int. Shipbuild. Prog. 29 (7), 166–170.
Hu, X., 1986. The influence of shallow water channel and narrow channel on ship resistance. Water Transp. Eng. 6, 27–29 (in Chinese).
International Maritime Organization, 2010. Prevention of air Pollution from Ships: Assessment of IMO Efficiency Measures for the Control of GHG Emissions from Ships. IMO, London.
Kornelakis, A., 2010. Multiobjective Particle Swarm Optimization for the optimal design of photovoltaic grid-connected systems. Sol. Energy 84 (12), 2022–2033.
Kwon, Y.J., 2008. Speed loss due to added resistance in wind and waves. Naval Architect. 3, 14–16.
Lindstad, H., Asbjørnslett, B., Strømman, A.H., 2011. Reductions in greenhouse gas emissions and cost by shipping at lower speeds. Energy Policy 39, 3456–3464.
Liu, C., Zheng, H. Negenborn, R.R., Chu, X., Wang, L., 2015. Trajectory tracking control for underactuated surface vessels based on nonlinear Model Predictive Control. In: Proceedings of the 6th International Conference on Computational Logistics (ICCL'15), Delft, The Netherlands, pp. 160–180.
Lu, R., Turan, O., Boulougouris, E., Banks, C., Incecik, A., 2015. A semi-empirical ship operational performance prediction model for voyage optimization towards energy efficient shipping. Ocean Eng. 110, 18–28.
Magirou, E.F., Psaraftis, H.N., Bouritas, T., 2015. The economic speed of an oceangoing vessel in a dynamic setting. Transport. Res. Part B: Methodol. 76, 48–67.
Marine Environment Protection Committee, 2014. Prevention of air pollution from ships (Third IMO GHG Study 2014). Marine Environment Protection Committee, London.
Meng, Q., Du, Y., Wang, Y., 2016. Shipping log data based container ship fuel efficiency modeling. Transport. Res. Part B: Methodol. 83, 207–229.
Negenborn, R.R., Maestre, J.M., 2014. Distributed model predictive control–An overview and roadmap of future research opportunities. IEEE Control Syst. Mag. 34 (4), 87–97.
Norstad, I., Fagerholt, K., Laporte, G., 2011. Tramp ship routing and scheduling with speed optimization. Transport. Res. Part C: Emerg. Technol. 19 (5), 853–865.
Psaraftis, H.N., Kontovas, C.A., 2013. Speed models for energy-efficient maritime transportation: a taxonomy and survey. Transport. Res. Part C: Emerg. Technol. 26, 331–351.
Psaraftis, H.N., Kontovas, C.A., 2014. Ship speed optimization: concepts, models and combined speed-routing scenarios. Transport. Res. Part C: Emerg. Technol. 44 (4), 52–69.
Ronen, D., 2011. The effect of oil price on containership speed and fleet size. J. Operat. Res. Soc. 62 (1), 211–216.

Sun, X., Yan, X., Wu, B., Song, X., 2013. Analysis of the operational energy efficiency for inland river ships. Transport. Res. Part D: Transp. Environ. 22, 34–39.
Townsin, R.L., Moss, B., Wynne, J.B., 1975. Monitoring the Speed Performance of Ships. University of Newcastle, England.
UNCTAD/RMT/2016, “Review of Maritime Transport 2016,” United Nations publication.
Wang, S., Meng, Q., 2012. Sailing speed optimization for container ships in a liner shipping network. Transp. Res. Part E: Log. Transport. Rev. 48 (3), 701–714.
Wang, K., Yan, X., Yuan, Y, Tang, D., Ma, D., 2015a. Design of ship energy efficiency monitoring and control system considering environmental factors. In: Proceedings of the 3rd International Conference on Transportation Information and Safety (ICTIS 2015). June, Wuhan, China.
Wang, K., Yan, X., Yuan, Y., 2015b. Study and simulation on the energy efficiency management control strategy of ship based on clean propulsion system. In: Proceedings of the ASME 34th International Conference on Ocean, Offshore and Arctic Engineering (OMAE 2015). St. John's, Newfoundland, Canada.
Wang, K., Yan, X., Yuan, Y., 2015c. Fuzzy logic method for ship energy efficiency: decision-making model to determine optimal engine speed. Sea Technol. 56 (11), 45–46.
Wang, K., Yan, X., Yuan, Y., Li, F., 2016a. Real-time optimization of ship energy efficiency based on the prediction technology of working condition. Transport. Res. Part D: Transp. Environ. 46, 81–93.
Wang, K., Yan, X., Yuan, Y., Tang, D., 2016b. Optimizing ship energy efficiency: Application of particle swarm optimization algorithm. Proc. Inst. Mech. Eng. Part M J. Eng. Maritime Environ (Doi: 10.1177/1475090216638879).
Wang, K., Jiang, X., Yan, X., Lodewijks, G., Yuan, Y., Negenborn, R.R., 2017a. PSO-based method for safe sailing route and efficient speeds decision-support for sea-going ships encountering accidents. In: 14th IEEE International Conference on Networking, Sensing and Control. Calabria, Southern Italy, May 2017.
Wang, K., Yan, X., Yuan, Y., Jiang, X., Lodewijks, G., Negenborn, R.R., 2017b. Study on route division for ship energy efficiency optimization based on big environment data. In: Proceedings of the 4th International Conference on Transportation Information and Safety (ICTIS 2017). doi: 10.1109/ICTIS.2017.8047752, pp. 111–116
Xin, J., Negenborn, R.R., Lodewijks, G., 2015. Energy-efficient container handling using hybrid model predictive control. Int. J. Control 88 (11), 2327–2346.
Yan, X., Ma, F., Chu, X., 2011. Key technology of collecting traffic flow on the Yangtze River in real-time. Navigation China 35 (3), 301–308 (in Chinese).
Yan, X., Sun, X., Yin, Q., 2015. Multiparameter sensitivity analysis of operational energy efficiency for inland river ships based on backpropagation neural network method. Mar. Technol. Soc. J. 49, 148–153.
Yan, Z., Yan, X., Ma, F., et al., 2010. Green Yangtze River intelligent shipping information system and its key technologies. J. Transp. Inform. Saf. 29, 76–81 (in Chinese).
Zhao, F., Yang, W., Tan, W.W., Yu, W., Yang, J., Chou, S.K., 2016. Power management of vessel propulsion system for thrust efficiency and emissions mitigation. Appl. Energy 161 (7), 124–132.
Zheng, H., Negenborn, R.R., Lodewijks, G., 2016. Predictive path following with arrival time awareness for waterborne AGVs. Transp. Res. Part C: Emerg. Technol. 70, 214–237.
Zheng, H., Negenborn, R.R., Lodewijks, G., 2017. Closed-loop scheduling and control of waterborne AGVs for energy-efficient inter terminal transport. Transport. Res. Part E: Log. Transport. Rev. 105, 261–278.