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A R T I C L E I N F O

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A B S T R A C T

The optimization of ship energy consumption is attracting a great deal of attention, as societies seek to save energy and reduce emissions. Shipping companies are more concerned with the energy consumption of a ship fleet, as opposed to that of a single ship. Because the energy consumption of a fleet is influenced by multiple factors including environmental factors, port operations and transport demands, an improvement in a single ship's energy consumption does not necessarily mean that the overall energy consumption of a fleet is good. In addition, those factors are usually varying over time, making it hard to optimize the fleet's energy consumption by methods that do not consider these time-varying factors. Therefore, a bi-level distributed dynamic optimization method based on distributed model predictive control is proposed. Moreover, an upper-level optimization model for fleet operational decision-making and a lower-level dynamic optimization model of fleet energy consumption are established. Based on these, a control algorithm for the dynamic optimization of fleet energy consumption is developed. Finally, a case study is carried out to demonstrate the effectiveness of the method. It can further reduce the energy consumption of each ship by at least 1.1% and about 6.8% for the whole fleet.

1. Introduction

Waterway transportation, as the most fuel-efficient and economic way of shipping goods, has undergone great developments in recent years (Zheng et al., 2019). The worldwide seaborne transportation volume was about 10 billion tons in 2015 (UNCTAD/RMT, 2016). For the inland waterway transport, taking Yangtze River as an example, the amount of cargo transport was about 1.92 billion tons in 2013 (Tang, 2014). Apparently, Waterway transportation plays an important role in both nationwide and worldwide trades. However, the shipping industry is now obliged to reduce emissions of greenhouse gases and pollutants. A research conducted by IMO showed that more than 900 million tons of CO_2 is emitted by maritime transport in 2012, accounting for 2.6% of the total emissions over the world (MEPC, 2014). These emissions would increase about twice by 2050 if no actions were taken (MEPC, 2014). Among others, the total emissions from all ships on the Yangtze River would be more than 5 million tons (Cai, 2010). Meanwhile, confronted with the depressed market, shipping companies are making every effort to control the fuel cost, the main component of their operating costs (Lützen et al., 2017; Johnson et al., 2014). Therefore, there is an increasing need to reduce the fuel consumption and CO_2 emissions (Poulsen and Johnson, 2016).

In recent years, some research has been done on the fleet energy consumption optimization and management (Ronen, 2011; Andersson et al., 2015; Song and Yue, 2016; Wang et al., 2013; Coraddu et al., 2014; Song et al., 2015; Wang and Meng, 2012a; Wen et al., 2017; Xia et al., 2015). Frangopoulos (2018) carried out a detailed analysis of the optimization of energy systems, including static optimization and dynamic optimization method, and optimization in modeling of energy systems and modeling for optimization and so on. It is important for the research and development of the modeling and optimization of energy systems. In addition, Sakalis and Frangopoulos (2018) proposed a novel intertemporal modeling and optimization approach for the integrated energy systems in order to achieve the analysis and optimization of energy systems. Lindstad et al. (2011) investigated the influence of

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Nomenclature

k	The serial number of time steps
$j\#$	The serial number of ships
t	Time at different time step (h)
V_g	Sailing speed to ground (m/s)
V_s	Sailing speed to water (m/s)
S_{leg}	Distance of the different legs (m)
R_T	Calm water resistance (N)
R_F	Frictional resistance (N)
R_{APP}	Appendage resistance (N)
R_W	Resistance for breaking waves (N)
R_B	Resistance due to bulbous bow (N)
R_{TR}	Resistance of stern leaching (N)
R_A	Ship related resistance (N)
k_1	Viscous resistance factor of the ship
R_{wave}	Wave adding resistance (N)
F_r	Froude number (Dimensionless)
h	Height of wave (m)
L_{wl}	Length of waterline (m)
ρ	Water density (kg/m^3)
S_W	Wet area of the ship (m^2)
R_{wind}	Wind resistance (N)
C_{wind}	Coefficient of wind resistance
ρ_{air}	Air density (kg/m^3)
A_T	Windward area (m^2)
V_{wind}	Relative wind speed (m/s)
$R_{shallow}$	Resistance as for shallow water (N)
R_{deep}	Resistance as for deep water (N)
f_s	Conversion coefficient
H	Water depth (m)
d	Ship draft (m)
R	Total resistance of the ship (N)
P_B	Power of the main engine (kW)
K	Number of the propellers
K_Q	Coefficient of torque
w	Wake coefficient
η_S	Shaft transfer efficiency
η_G	Gearbox efficiency
η_R	Efficiency of rotation
K_T	Thrust coefficient
J	Propeller advance coefficient
t	Coefficient of thrust deduction
q_{main}	Fuel consumption of main engine (g/m)
W_{load}	Cargo mass (t)
$\tilde{V}_w$	Average water speed (m/s)
$\tilde{V}_{wind}$	Average wind speed (m/s)
$\tilde{H}$	Average water depth (m)
$\tilde{h}$	Average wave height (m)
g_{main}	Fuel consumption rate (g/kWh)
T_{total}	Total operational time of a voyage (d)
T_{nav}	Sailing time (d)
T_{limit}	Limit of the sailing time of the ship (d)
V_w	Water speed (m/s)
T_{wait}	Waiting time in the port (d)
T_{load}	Cargo loading and unloading time (d)
S	Distance of the whole voyage (m)
η^L	Loading efficiency (t/d)
η^U	Unloading efficiency (t/d)
q_{aux}	Fuel consumption of auxiliary engines (t)
g_{aux}	Fuel consumption per unit of time (t/d)
N	Number of ships in the fleet
$T_{total,\ limit}$	Limit of the total fleet operational time (d)
$W_{load,\ total}$	Total cargo mass of the fleet (t)
W_{load}	Cargo mass of the ship (t)
n_{min}	Minimum engine speed (r/min)
n_{max}	Maximum engine speed (r/min)
V_{min}	Minimum sailing speed (m/s)
V_{max}	Maximum sailing speed (m/s)
V_{water}	Water speed (m/s)
V_{wind}	Wind speed (m/s)
H	Water depth (m)
h	Wave height (m)
M	The number of steps
Q_{total}	Total energy consumption (t)
τ	Current iteration times
$\tilde{X}$	Position of the particle
$\tilde{p}_{best}$	The previous optimum
$\tilde{g}_{best}$	The global optimum
r_1, r_2	Random numbers between 0 and 1
c_1, c_2	Learning factors (Dimensionless)
$\tilde{V}$	The updating speed (Dimensionless)
w	Weight of inertia (Dimensionless)
w_{max}	Maximal inertia factor
w_{min}	Minimal inertia factor
$iter_{current}$	Current number of iteration times
$iter_{max}$	Maximal number of iteration times
Dt_j	Deadweight of the $j\#$ ship (t)
C_{carbon}	CO_2 conversion rate of the fuel
M_{CO2}	Amount of CO_2 emissions (t)
$Y_s(k)$	System state at time step k
$S_{total}(k)$	Total sailing distance at time step k (m)
$d_s(k)$	Disturbance of the system at time step k
$u_s(k)$	Control input at time step k

speed on the emissions of greenhouse gases and operating costs for different kind of ships. Their results indicate that maritime industry can achieve a significant reduction in CO_2 emissions. Cepeda et al. (2017) studied the impact of speed reduction on fleet economy and emissions by establishing a simulation model of a fleet. The result shows that the fleet can operate with higher efficiency when the speed reduction strategy is adopted. Although sailing speed is the major factor for ship energy consumption, other factors such as the environmental conditions and port operations also make an influence. Wang and Meng (2012b) suggested that energy consumption could be different even with the same speed due to the different environmental conditions, and established a non-linear model, in order to achieve speed optimization for container ships. Qi and Song (2012) studied on the design optimization of vessel schedule by accounting for the stochastic port time and frequency requirement, for reductions in both total energy consumption and emissions. Meng et al. (2016) proposed an effective optimization method based on a study on the interrelation between energy consumption and its influencing factors (speed, environmental conditions, and displacement) by analyzing shipping log data. Fleet energy consumption is not only related to speed and navigational environment, but also to ship loading, engine speed, sailing time, port operation time and market transport demand. In general, the above-mentioned optimization methods only considered one or a few influencing factors on the sea-going fleet energy consumption from the point of view of maritime logistics. Few studies, however, have addressed the comprehensive impact of multiple factors. In addition, these factors are usually dynamic

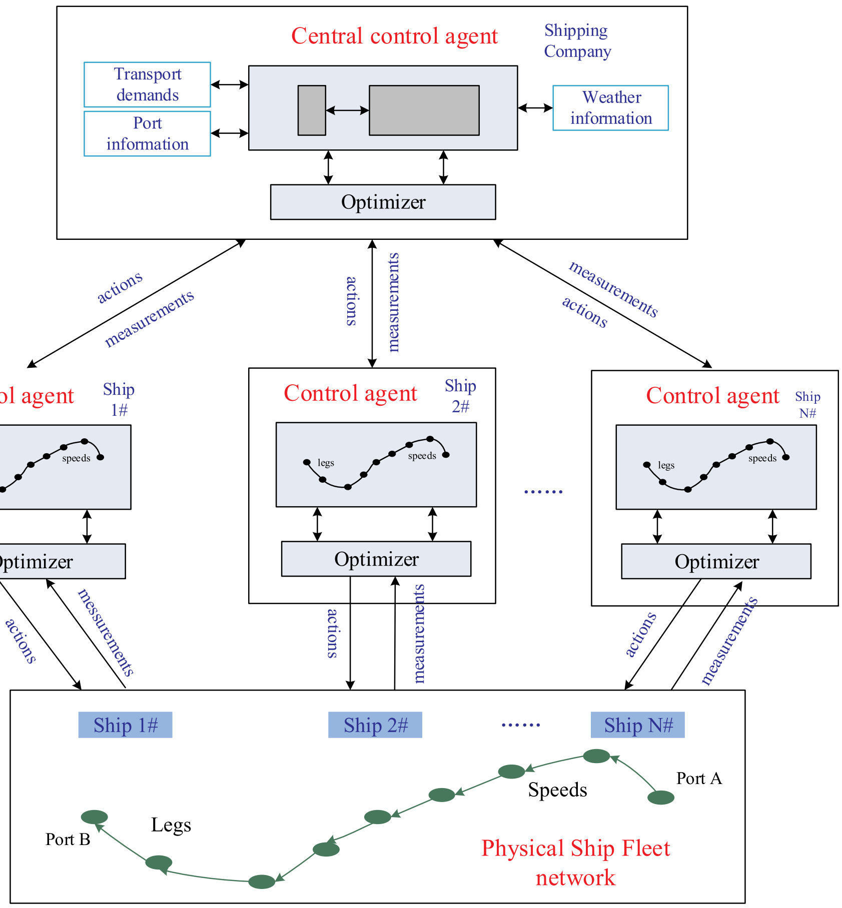

Fig. 1. The bi-level distributed dynamic optimization for the fleet energy consumption.

with a high degree of randomness. In this regard, however, research is still lacking on the dynamic optimization of fleet energy consumption.

In addition, compared with sea-going ship fleets, the sailing speeds for inland ship fleets are harder to optimize, due to the more complicated environmental conditions of the inland waterway and the uncertainty in the port operations (Wang et al., 2015). Sun et al. (2013) studied the energy consumption of an inland river ship in various sailing states and identified the influence of navigational environment and speed on the fuel consumed by an inland river ship. Yan et al. (2015) analyzed the sensitivity of the weather factors on affecting the ship energy consumption using a machine learning method. Wang et al. (2017b) investigated a sailing speed optimization method based on route division through big data analysis that further promoted the development of the energy consumption optimization of inland river ships accounting for multiple environmental factors. Despite the fruitful achievements on energy consumption optimization for a single inland river ship, there has been little study on the inland river ship fleets, let alone the dynamic optimization method considering multiple time-varying influencing factors. This paper aims to fill this gap. The integrated models we established could be used for the strategic optimization managements for the inland river ship fleet.

In support of this approach on the dynamic optimization method considering multiple time-varying influencing factors, we develop a bi-level optimization model incorporating a high-level optimization model for operational decision-making and a low-level dynamic optimization model for energy consumption. For the dynamic optimization and control problem, the model predictive control (MPC) has attracted extensive research, because of its better dynamic control performance and the ability of compensating for disturbances caused by dynamic factors (Negenborn et al., 2008; Xin et al., 2015; Zheng et al., 2016; Liu et al., 2015). In the practical operation, it is difficult to communicate effectively between ships and to achieve the centralized control from the shipping company. Therefore, we propose to adopt DMPC to optimize the energy consumption for each ship in the fleet. DMPC is a control strategy that can deal with control problems in large-scale systems caused by organizational couplings between different parties, limited control access and communication ability of different parties (Li et al., 2016). DMPC strategies have been adopted in many different controlled systems and applications, giving good performances (Spudić et al., 2015; Christofides et al., 2013; Zheng et al., 2017; Souza et al., 2015; Real et al., 2013; Negenborn and Maestre, 2014). To the best of our knowledge, no one has applied DMPC strategies in the operation optimization of ship fleets for reducing energy consumption and CO_2 emissions. In this paper, this approach is proposed to take for the dynamic optimization for inland river ship fleets.

This paper is an extension to the authors' earlier work Wang et al. (2016, 2018). The contribution of this paper is twofold. From theoretical perspective, we established a fleet energy consumption model accounting for multiple varying influencing factors. The established model can illustrate the fleet energy consumption under different operational states effectively. From the practical viewpoint, we generalized the optimization method for a single ship to a system-level distributed dynamic optimization for a fleet by adopting the DMPC strategy based on the updated operational information. Our control algorithm and controller can obtain the dynamic optimization for fleet energy consumption under continuously changing conditions. The proposed bi-level distributed dynamic optimization method could assist ship owners in fleet-wide energy consumption optimization, with the capability of decision-making for operation optimization and energy saving.

This paper is organized as follows. The method proposed in this

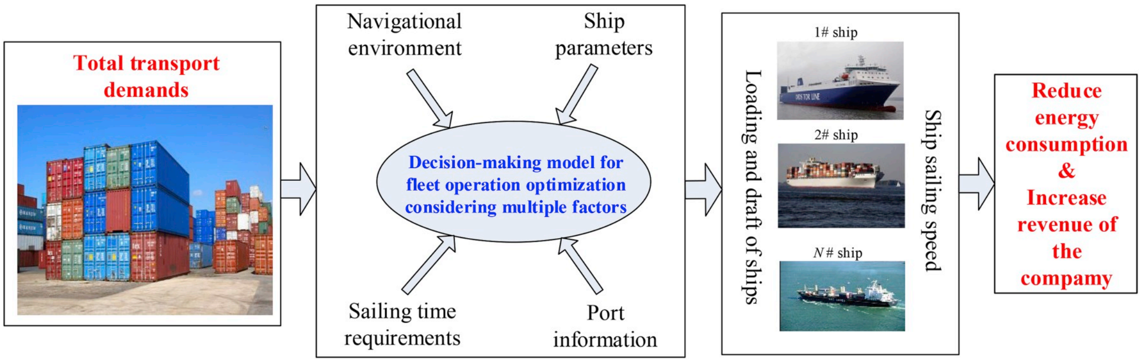

Fig. 2. Illustration of the fleet operation optimization method.

paper is briefly illustrated in Section 2. Then, a bi-level optimization model incorporating a fleet operational decision-making model and energy consumption optimization under time-varying operational conditions is established in Section 3. Subsequently, the dynamic optimization algorithm and controller based on DMPC strategy are designed in Section 4. Afterwards, a case study is carried out to validate the proposed dynamic method for fleet energy consumption optimization in Section 5. Finally, conclusions and the future research work are detailed in Section 6.

2. Method

The energy consumed by a fleet is related to multiple influencing factors, such as transport demands, environmental factors, port information and ship operational conditions. These factors are usually continuously varying over time. Moreover, the management of fleet energy consumption involves fleet operation optimization decision-making by the shipping company and single-ship navigation optimization by the controller on each ship. Only by overall management and optimization can we optimize the energy consumption, meanwhile meeting the transport demands of the fleet. Therefore, a bi-level distributed dynamic optimization method for fleet energy consumption is proposed in this paper, as showed in Fig. 1. It mainly includes an upper-level optimization model for the fleet operational decision-making, and a lower-level dynamic optimization model for the fleet energy consumption considering multiple influencing factors.

2.1. *Upper-level optimization method for the fleet operation decision-making*

The upper-level optimization method of fleet operation refers to the decisions made by the shipping company to increase revenue and reduce energy cost. As shown in Fig. 2, given the certain transport demand of fleet, shipping company could achieve the fleet operation optimization through the established fleet operation decision-making model considering multiple influencing factors. Those factors include port information (waiting time, loading and unloading efficiency in the port), navigational environment, total time requirement and specific parameters of each ship. Finally, the optimal cargo mass as well as sailing speed of each ship would be determined to improve economy and energy consumption of the fleet, meanwhile ensuring the completion of cargo transport tasks within the scheduled time. In this level, the sailing speed optimization is based on the constant environmental factors and port information, not considering the dynamics of these factors. Therefore,

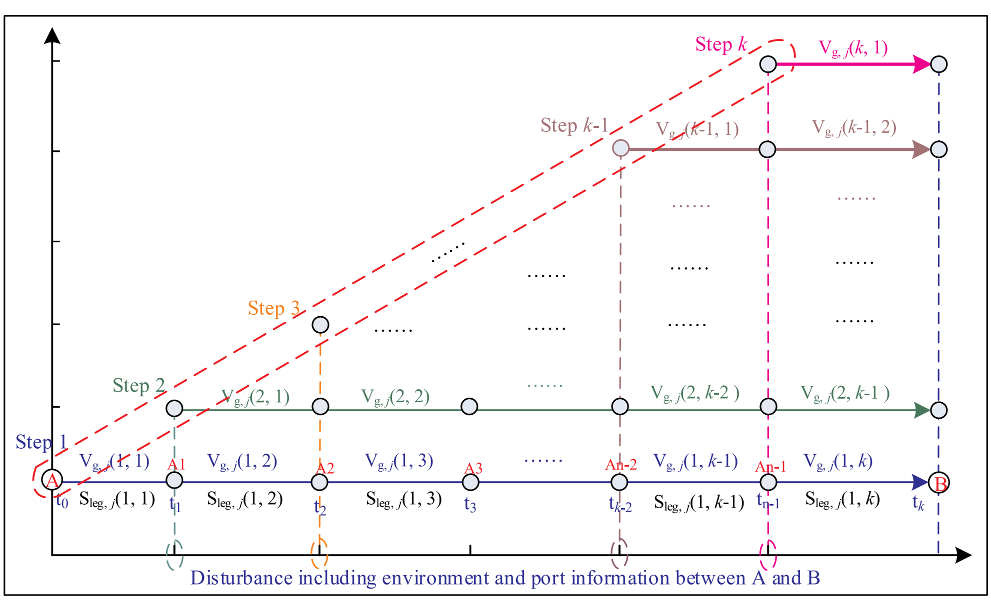

Fig. 3. The dynamic optimization process for fleet energy consumption.

the decided sailing speeds are constant along the entire voyage, and there are still potentials for better fleet energy efficiency when considering the dynamics of those influencing factors. In order to complete the transportation task within the scheduled time, the sailing time under the decided sailing speed would be set as the time constraint of each ship for the lower-level navigation optimization model.

2.2. Lower-level dynamic optimization method for the fleet energy consumption

In the lower-level dynamic optimization method, the dynamics of environmental factors and port information are both considered, thus to reach the high potential of energy consumption optimization. A route could be divided into different segments according to the k time steps. As shown in Fig. 3, at step 1, the optimal sailing speeds under the current operational conditions can be determined by the constructed optimization model and solving method, utilizing the information on navigational environment and port operation. The j# ship will be operated at this optimal speed $V_{g,j}(1,1)$ in the first leg within this step. Afterwards, the updated environmental conditions and port information would be available again before the ship arrives at position A1. Then, the optimal sailing speeds corresponding to the updated information for the left n-1 sailing legs will be obtained by re-running the optimization model and solution method. When the j# ship reaches position A1, it would be controlled to sail at the optimized sailing speed $V_{g,j}(2,1)$ in the second leg within the second step. Similarly, continuous optimizations and controlling will be carried out until the ship arrives at the destination. In this way, from the time-varying information on the navigational environment and port operation, a dynamic optimization in the energy consumption can be achieved. The DMPC strategy based dynamic optimization can keep the optimal solutions at each step, namely, each ship could operate at the optimal speeds during each step.

Through the above-mentioned bi-level distributed dynamic optimization method, the full potential of energy consumption optimization for the fleet can be realized. The fleet operational decisions can be made, taking various influencing factors into account. In addition, the dynamic energy consumption optimization for each ship can be achieved in a distributed way, according to the updated weather conditions and port operational information. These two models, among others, are the key to the dynamic optimization for the fleet energy consumption.

3. Dynamic optimization model of fleet energy consumption

3.1. Fleet operational decision-making model considering multiple influencing factors

The fleet operational decision-making model is aimed at reducing the energy consumption by determining the optimal sailing speeds and cargo loads. The operational conditions including the navigational environment and port operation have a huge influence on the speed optimization results and thus the fuel consumption. The effect of operational conditions is mainly due to their impact on the ship resistance. The fuel consumption can be obtained through the energy conversion analysis among hull-propeller-engine by analyzing the resistance of the ship under specific sailing speeds and navigational conditions. The total resistance, including the resistance in calm water (Holtrop and Mennen, 1982), resistance of wave and wind (Kwon, 2008), resistance in shallow water (Hu, 1986), can be expressed as follows:

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

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

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

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

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

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

As for a given sailing speed, the generated power and related energy consumption of the main diesel engine is expressed as (Wang et al., 2018):

$$P_{B,j} = \frac{R_j \cdot \left(V_{g,j} \pm \tilde{V}_{w,j}\right) \cdot K_{Q,j} \cdot 2\pi \cdot \left(1-w_j\right)}{K_j \cdot \eta_{S,j}\eta_{G,j}\eta_{R,j} \cdot K_{T,j} \cdot J_j \cdot \left(1-t_j\right)} \tag{7}$$

$$q_{main,j} = \frac{R_j \cdot \left(V_{g,j} \pm \tilde{V}_{w,j}\right) \cdot K_{q,j} \cdot 2\pi \cdot \left(1-w_j\right)}{\eta_{S,j}\eta_{G,j}\eta_{R,j} \cdot K_{t,j} \cdot J_j \cdot \left(1-t_j\right) \cdot V_{g,j}} \cdot g_{main,j} = F_{q,j}\left(W_{load,j}, V_{g,j}, \tilde{V}_{w,j}, \tilde{V}_{wind,j}, \tilde{H}_j, \tilde{h}_j, g_{main,j}\right) \tag{8}$$

In addition, under a specific sailing speed, the total operational time of the ship for a voyage can be expressed as:

$$T_{total,j} = T_{nav,j} + T_{wait,j} + T_{load,j} = S\Big/V_{g,j}\Big/3600 + T_{wait,j} + W_{load,j}\Big/\eta_j^L + W_{load,j}\Big/\eta_j^U \tag{9}$$

Moreover, the energy consumption of the auxiliary engines can be expressed as:

$$q_{aux,j} = T_{total,j} \cdot g_{aux,j} \tag{10}$$

Above all, the upper-level optimization is nonlinear with the minimum total fuel consumption of the ship fleet as the objective, as shown:

$$\min \quad Q_{total} = \sum_{j=1}^{N}\left(F_{q,j}\left(W_{load,j}, V_{g,j}, \tilde{V}_{w,j}, \tilde{V}_{wind,j}, \tilde{H}_j, \tilde{h}_j, g_{main,j}\right) \cdot S + q_{aux,j}\right) \tag{11}$$

Subject to the following constraints:

$$V_{g,j} \cdot T_{nav,j} = S \tag{12}$$

$$T_{total} = \sum_{j=1}^{N}\left(T_{total,j}\right) < T_{limit,total} \tag{13}$$

$$\sum_{j=1}^{N} W_{load,j} = W_{load,total} \tag{14}$$

$$n_{min,j} < f_{engine\_speed}\left(V_{g,j} \pm \tilde{V}_{w,j}\right) < n_{max,j} \tag{15}$$

$$V_{min,j} < V_{g,j} \pm \tilde{V}_{w,j} < V_{max,j} \tag{16}$$

In **Eq.** (11), the cargo loading and sailing speeds of each ship are the decision variables. $F_{q,j}()$ means the energy consumption function that take the cargo mass, ship sailing speed, water and wind speed, water depth and wave height as the input variables, and take the energy consumption of the main diesel engine as the output variable. **Constraints** (12)–(14) ensure that the j# ship could complete its entire

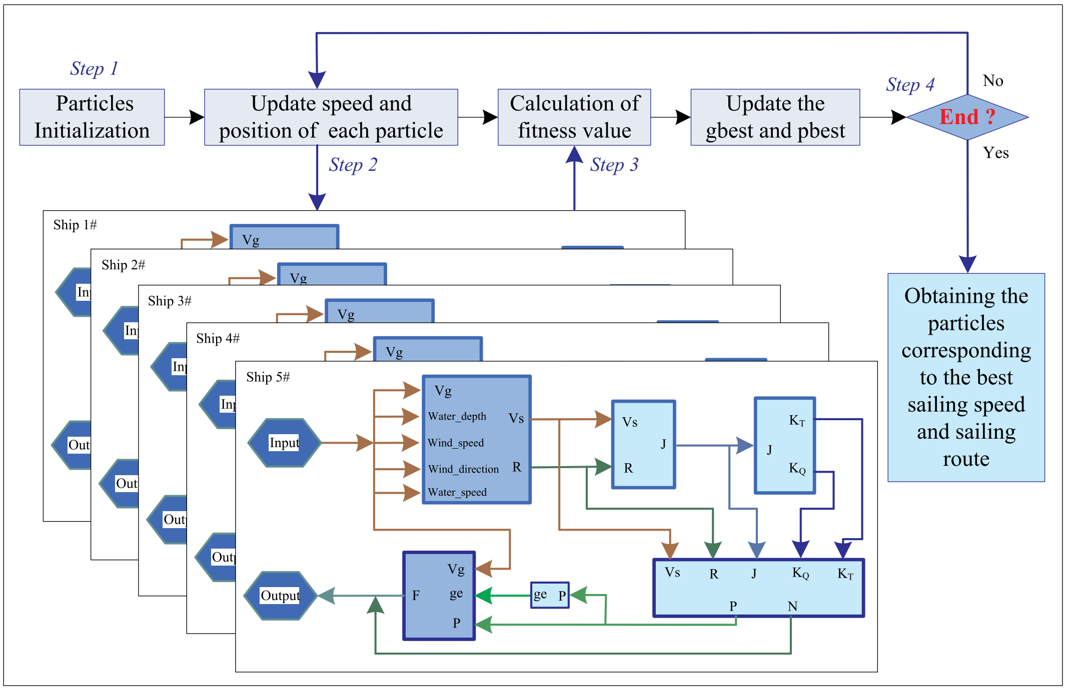

Fig. 4. The solving process of the nonlinear optimization model based on PSO.

voyage and transport demands within the scheduled time. **Constraints** (15) and (16) are the physical constraints for the engine speed and sailing speed of the j# ship respectively, in order to avoid overloading.

3.2. Dynamic optimization model of fleet energy consumption under time-varying conditions

According to **Eq.** (7), the main engine output power of the j# ship at time step k can be obtained as:

$$P_{\mathrm{B},jk}=\frac{R_{jk}\cdot V_{\mathrm{S},jk}\cdot K_{\mathrm{Q},jk}\cdot 2\pi\cdot\left(1-w_j\right)}{K_j\cdot\eta_{\mathrm{S},jk}\cdot\eta_{\mathrm{G},jk}\cdot\eta_{\mathrm{R},jk}\cdot K_{\mathrm{T},jk}\cdot J_{jk}\cdot\left(1-t_j\right)} \tag{17}$$

On this basis, the consumed fuel of the main diesel engine per unit of distance for the j# ship at time step k is shown as:

$$\begin{aligned} q_{\mathrm{main},jk}&=\frac{R_{jk}\cdot\left(V_{\mathrm{g},jk}\pm V_{\mathrm{w},jk}\right)\cdot K_{\mathrm{Q},jk}\cdot 2\pi\cdot\left(1-w_j\right)}{\eta_{\mathrm{S},jk}\cdot\eta_{\mathrm{G},jk}\cdot\eta_{\mathrm{R},jk}\cdot K_{\mathrm{T},jk}\cdot J_{jk}\cdot\left(1-t_j\right)\cdot V_{\mathrm{g},jk}}\cdot g_{\mathrm{main},jk}\\ &=G_{\mathrm{q},jk}\left(V_{\mathrm{g},jk},V_{\mathrm{w},jk},V_{\mathrm{wind},jk},H_{jk},h_{jk},g_{\mathrm{main},jk}\right)\end{aligned} \tag{18}$$

In addition, the total energy consumption of the auxiliary engine of the j# ship can be expressed as:

$$q_{aux,j}=T_{\mathrm{limit},j}\cdot g_{aux,j} \tag{19}$$

Then, the remaining navigational time of the j# ship at time step k is:

$$T_{\mathrm{nav},jk}=T_{\mathrm{limit},j}-T_{\mathrm{wait},jk}-W_{\mathrm{load},j}/\eta_{jk}^{\mathrm{L}}-W_{\mathrm{load},j}/\eta_{jk}^{\mathrm{U}}-\sum_{i=1}^{k-1}\left(T_{\mathrm{nav},\ ji}\Big/\left(M-k+1\right)\right) \tag{20}$$

Above all, the dynamic optimization of the fleet energy consumption is also nonlinear with the minimal total energy consumption as the objective, as expressed by:

$$\min\ Q_{\mathrm{total},jk}=\sum_{i=1}^{M-k+1}\left(G_{\mathrm{q},ji}\left(V_{\mathrm{g},ji},V_{\mathrm{w},ji},V_{\mathrm{wind},ji},H_{ji},h_{ji},g_{\mathrm{main},ji}\right)\cdot V_{\mathrm{g},ji}\cdot\frac{T_{\mathrm{nav},jk}}{M-k+1}\right)+\left(T_{\mathrm{nav},jk}+T_{\mathrm{wait},jk}+W_{\mathrm{load},j}\Big/\eta_{jk}^{\mathrm{L}}+W_{\mathrm{load},j}\Big/\eta_{jk}^{\mathrm{U}}\right)\cdot g_{\mathrm{aux},j}\forall k\in\{1,2,\ldots,M\} \tag{21}$$

Subject to the following constraints:

$$\sum_{i=1}^{M-k+1}\left(V_{\mathrm{g},ji}\cdot\frac{T_{\mathrm{nav},jk}}{M-k+1}\right)=S-S_{\mathrm{total},j(k-1)} \tag{22}$$

$$N_{\mathrm{min},j}<f_{\mathrm{engine\_speed}}\left(V_{\mathrm{g},jk}\pm V_{\mathrm{w},jk}\right)<N_{\mathrm{max},j} \tag{23}$$

$$V_{\mathrm{min},j}<V_{\mathrm{g},jk}\pm V_{\mathrm{w},jk}<V_{\mathrm{max},j} \tag{24}$$

For this optimization model, the optimization variables are the sailing speeds of each ship at each time step. **Constraint** (22) ensures the ship reaches the destination within the scheduled time. **Constraints** (23) and (24) are the physical constraints for the main diesel engine and navigation speed of the j# ship respectively, which can avoid overloading.

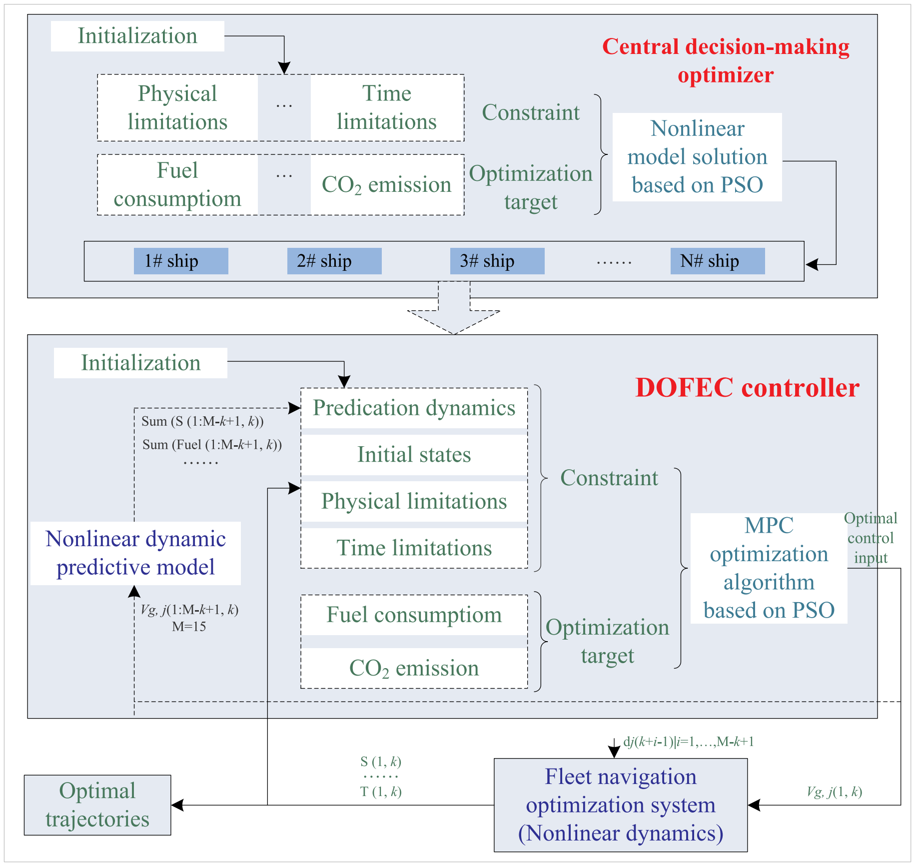

Fig. 5. The dynamic optimization controller for the fleet energy consumption optimization.

The adopted DMPC strategy can be used to predict the results of the energy consumption system according to the historical data, including the current state, and the current and future inputs and disturbance of the system. For the dynamic optimization of fleet energy consumption in this paper, the current state mainly includes the distance of sailing and weather information as well as port operational information, which can be expressed as:

$$Y_{s,j}(k) = S_{\text{total},j}(k) = \sum_{i=1}^{k}\left(V_{g,j(k-i+1)}\cdot\frac{T_{\text{nav},j(k-i+1)}}{M-k+i}\right) \tag{25}$$

$$d_{s,j}(k)=\left\{V_{g,j(k+i-1)},V_{w,j(k+i-1)},V_{\text{wind},j(k+i-1)},H_{j(k+i-1)},h_{j(k+i-1)},T_{wait,j(k+i-1)}\right\}\ \forall i\in\{1,\ 2,\ \ldots,M\} \tag{26}$$

Thus, the dynamics of the energy consumption optimization system at step k can be represented as follows:

$$Y_{s,j}(k+1)=\mathrm{F}_{s,j}\left(Y_{s,j}(k),u_{s,j}(k),d_{s,j}(k)\right) \tag{27}$$

4. Distributed control algorithm and controller design

4.1. Control algorithm

The DMPC based control algorithm for dynamic optimization of fleet energy consumption is developed, as shown in the Algorithm 1.

As shown in Fig. 4, the solving process of the upper-level nonlinear optimization model based on the modified Particle Swarm Optimization

Algorithm 1

1. Initialize the state of fleet operation decision-making system (including the transport demands, navigational environment and the port operation information);
2. Solve the established upper-level optimization model of fleet operation considering multiple factors, in order to obtain the cargo loading mass and sailing speed of each ship. Meanwhile determine the sailing time constraint for the lower-level optimization;
3. **for** j=1:N do
4. When the time step is k=0, the state and disturbance of the system are initialized (including navigational environment, port operation information and sailing time constraints);
5. **while** $k \le M$ do
6. Obtain the current state $Y_{s,j}(k)$ and disturbance $d_{s,j}(k)$ of the system at time step k, and obtain the optimal solutions ($V_{g,jk}$,…, $V_{g,jM}$) as the input of the system ($u_{s,j}(k)$,…, $u_{s,j}(M)$);
7. Only adopt the optimal decision $u_{s,j}(k)$, leading to the new system state $Y_{s,j}(k+1)$;
8. $k \leftarrow k+1$ and return to the Step 5;
9. **end while**
10. **end for**

(PSO) mainly includes:

Step 1: Initialize N_S particles in 2N dimensions, and obtain the optimal values of individual and group by **Eq.** (11);

Step 2: Update the speed and location of the particle. These particles' positions are updated based on their speeds, giving:

$$\tilde{V}^{\tau+1} = w \cdot \tilde{V}^{\tau} + c_1 \cdot r_1\left(\tilde{p}^{\tau}_{\text{best}} - \tilde{X}^{\tau}\right) + c_2 \cdot r_2\left(\tilde{g}^{\tau}_{\text{best}} - \tilde{X}^{\tau}\right) \quad \forall \tau \in \{1,\ 2,\ \cdots,\ \tau_{\max} - 1\} \tag{28}$$

Table 1
Parameters of the target fleet.

Parameters	Ship 1#	Ship 2#	Ship 3#	Ship 4#	Ship 5#
Length (m)	77	85.88	85.88	90	99.8
Width (m)	15.8	15.84	15.84	16.2	16.25
Depth (m)	5.6	6	6	6	5
Deadweight (t)	3600	4830	4830	5130	4579
Engine power (kW)	528 × 2	600 × 2	600 × 2	720 × 2	528 × 2
Engine speed (r/min)	1200	1500	1500	1450	1200

$$\tilde{X}^{\tau+1} = \tilde{X}^{\tau} + \tilde{V}^{\tau+1} \quad \forall \tau \in \{1,\ 2,\ \cdots,\ \tau_{\max} - 1\} \tag{29}$$

In order to guarantee optimality of the results, the method of linear decreasing inertia weight is adopted in this paper, as shown in **Eq.** (30). At the beginning of iteration, the larger inertia weight is adopted to guarantee the strong global search ability of the algorithm, and in later iterations, the lower inertia weight is used to ensure the accurate local search of the algorithm, thus improving the accuracy of the algorithm.

$$w = w_{\max} - (w_{\max} - w_{\min}) \cdot iter_{\text{current}} / iter_{\max} \tag{30}$$

Step 3: Calculate the fitness values of the particles that meet the **Constraints** (12)-(16), and then obtain the updated optimal values of individual and population;

Step 4: Go to *Step 2* and repeat until the preset threshold or iteration times are reached. In this way, the optimal sailing speeds along the route and the loading weight of each ship can be achieved.

Similarly, the process of solving the lower-level nonlinear optimization model mainly includes the following steps:

Step 1: Initialize N_x particles in M-k+1 dimensions, and obtain the individual and group optimal values by calculating the fitness values of the particles through **Eq.** (21);

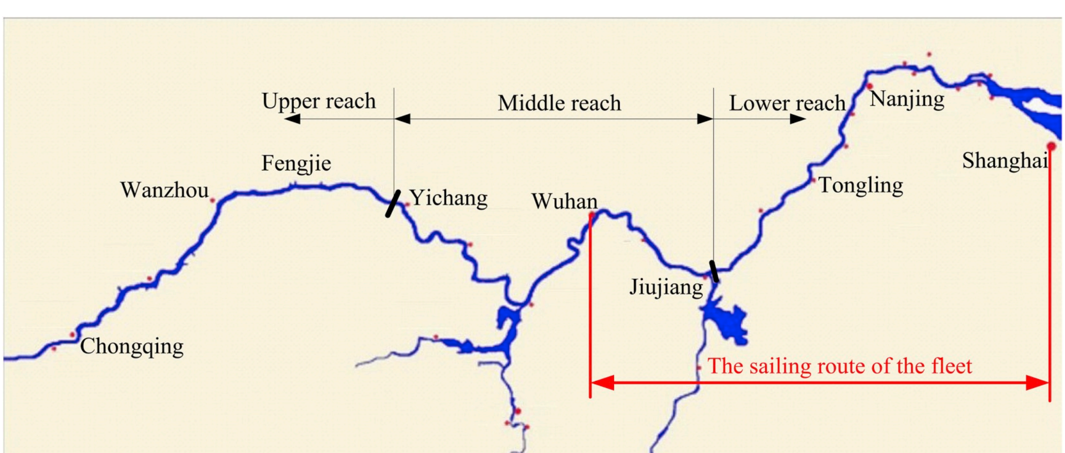

Fig. 6. The sailing route of the fleet.

Table 2
Navigational environment information and port operation information at different time steps.

Time steps	Navigational environment information at different positions																Port operation information				
	121.3169 E; 31.5706 N					121.3159 E; 31.5716 N					…	114.8045 E; 30.6127 N					Waiting time (d)				
	V_{wind} (m/s)	D_{wind} (deg)	H_w (m)	V_w (m/s)	H (m)	V_{wind} (m/s)	D_{wind} (deg)	H_w (m)	V_w (m/s)	H (m)		V_{wind} (m/s)	D_{wind} (deg)	H_w (m)	V_w (m/s)	H (m)	1 #	2 #	3 #	4 #	5 #
1	7.5	88	13	0.0	0.6	8.1	97	13	0.0	0.3	…	6.5	61	14	0.0	0.7	0.6	0.6	0.6	0.6	0.6
2	0.9	137	70	0.4	0.7	1.1	289	98	1.3	0.6	…	13.0	346	29	1.4	0.3	0.4	0.4	0.5	0.5	0.5
3	10.7	116	11	1.5	0.5	10.8	317	21	0.1	0.8	…	10.7	90	37	0.7	0.8	0.5	0.6	0.5	0.5	0.4
4	7.3	324	94	0.9	0.9	6.5	358	121	0.5	0.7	…	11.4	246	124	1.3	0.9	0.5	0.4	0.6	0.5	0.5
5	6.9	163	24	1.1	0.2	0.3	244	89	0.5	0.8	…	6.3	219	75	0.7	0.2	0.5	0.6	0.5	0.6	0.5
6	10.0	81	81	1.4	0.4	10.3	14	58	0.8	0.3	…	7.3	236	92	1.4	0.9	0.5	0.5	0.4	0.4	0.5
7	9.9	189	54	0.0	0.5	9.2	64	139	0.4	0.5	…	4.2	314	101	1.6	0.8	0.6	0.4	0.5	0.4	0.4
8	2.2	245	133	1.8	0.2	12.6	125	106	1.5	0.2	…	7.1	73	65	0.3	0.8	0.5	0.4	0.6	0.5	0.5
9	4.5	302	63	1.4	0.1	4.0	313	72	1.3	0.2	…	0.8	53	99	1.6	0.7	0.5	0.5	0.5	0.5	0.4

Table 3
Parameters for the upper-level operational decision-making model.

Parameters	c_1	c_2	w_{max}	w_{min}	$iter_{max}$	$\eta_j^{U/L}$ (t/d)	$T_{wait,j}$ (d)
Values	2	2	0.9	0.4	150	5000	0.5
Parameters	Dt_1 (t)	Dt_2 (t)	Dt_3 (t)	Dt_4 (t)	Dt_5 (t)	S (km)	$W_{load,total}$ (t)
Values	3600	4830	4830	5130	4579	1124.78	20672

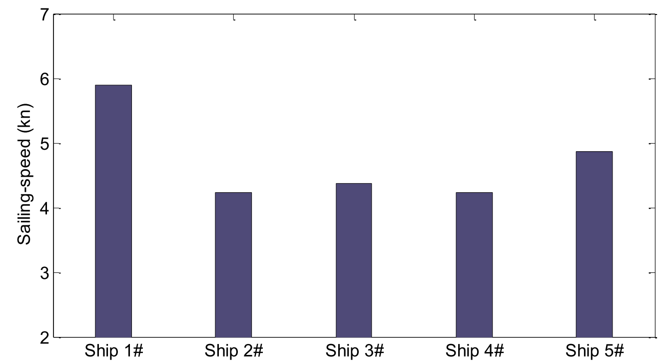

Fig. 7. The sailing speed of each ship along the entire route.

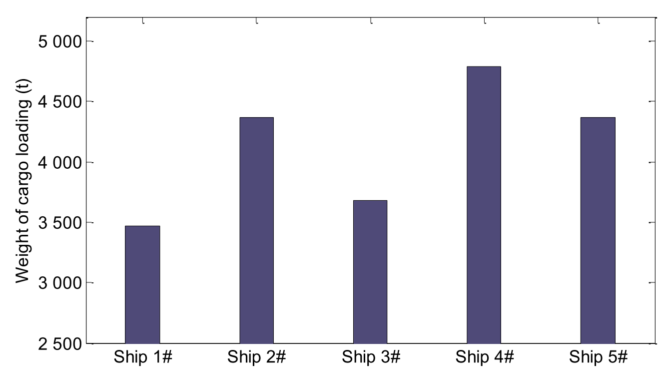

Fig. 8. The weight of cargo loading for each ship.

Table 4
The voyage time in the upper level and time constraint for the lower level.

Item	Ship 1#	Ship 2#	Ship 3#	Ship 4#	Ship 5#
Voyage time in the upper level (d)	6.183	8.227	7.752	8.392	7.447
Time constraint for the lower level (d)	6.183	8.227	7.752	8.392	7.447

Table 5
Parameters for the lower-level fleet energy consumption optimization.

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

Step 2: Update speeds and positions of the particles by **Eq.** (28) and **Eq.** (29) at each time step;

Step 3: Calculate the fitness values of the particles that meet the constraints (22)–(24), and then obtain the updated optimal values of individual and population;

Step 4: Go to *Step 2* and repeat until the algorithm reaches the preset

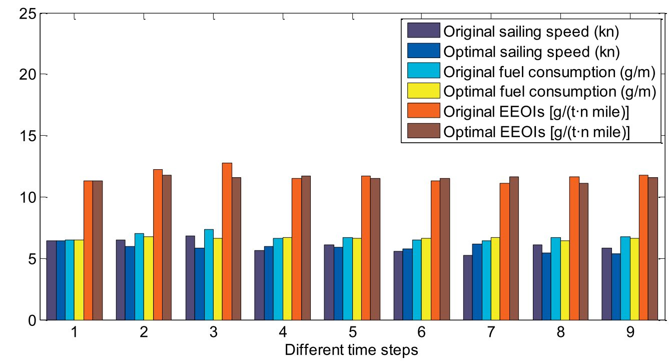

Fig. 9. The navigation optimization results of the 1# ship.

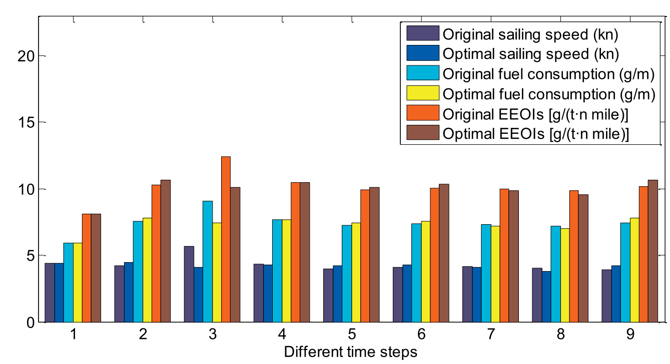

Fig. 10. The navigation optimization results of the 2# ship.

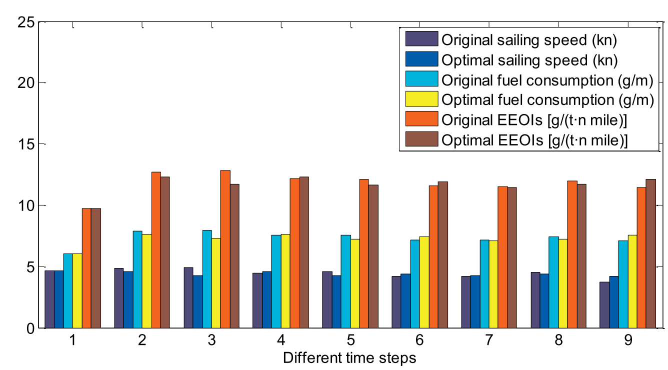

Fig. 11. The navigation optimization results of the 3# ship.

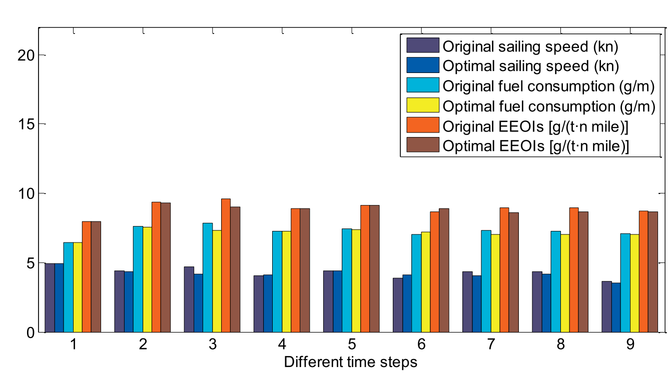

Fig. 12. The navigation optimization results of the 4# ship.

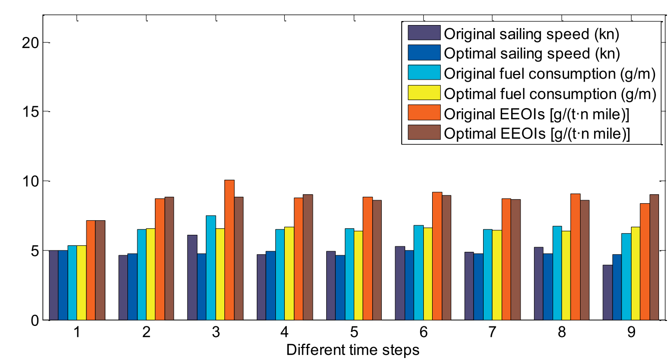

Fig. 13. The navigation optimization results of the 5# ship.

threshold or iteration times. In this way, the optimal speeds are achieved as $(V_{g,\,jk}, \ldots, V_{g,\,jM})$, which are also the system's inputs $(u_s(k), \ldots, u_s(M))$.

4.2. Controller design

According to the above-mentioned algorithms, a DMPC-based dynamic optimization method and controller for fleet energy consumption is proposed, as shown in Fig. 5. It includes a central decision-making optimizer and a dynamic optimization of fleet energy consumption (DOFEC) controller. Firstly, the central decision-making optimizer determines the optimal sailing speeds and load weights for each ship, thus to improve the economy under the sailing time and transport demands constraints. Then the upper-level optimal solutions are taken as the inputs of the controller for each ship. The controller achieves the optimal solutions at each step through the low-level optimization model, and then executes the first decision through the optimization system. This DOFEC controller can make up for disturbances resulting from the constantly changing weather conditions and port operations. Consequently, the dynamic optimization can be achieved, realizing the dynamic optimization of fleet energy consumption.

5. Case study

5.1. Numerical experiment

This paper takes as the research target a fleet consisting of five cargo ships from a major Chinese marine shipping company, sailing on the Yangtze River. The basic parameters of those ships are illustrated in Table 1.

The ship fleet sails from Shanghai port to Wuhan port along the Yangtze River, as shown in Fig. 6. The voyage time constraint is 38 days and the total transport amount is 20672 tons from the practical point of view. Under the normal weather condition, it usually takes about 8 h for the weather to change at a certain extent according to the weather analysis and so the total number of time steps is set as nine with about 8 h for each time step. In addition, based on the characteristic analysis on the environment and port operation data, the updated information on the navigational environment and port operation information at different time steps are shown in Table 2. This numerical study aims to demonstrate the validity of the dynamic optimization method.

5.2. Optimization result

5.2.1. Upper-level optimization result of fleet operation decision-making

The parameters required for the upper-level optimization in terms of the fleet operation decision making are shown in Table 3. By adopting the above-established model and solving method, we obtained the optimal sailing speeds along the entire route and the optimal cargo loading weights for each ship, as shown in Figs. 7 and 8, respectively.

Table 6
A comparison between the dynamic and static optimization results.

Items		Ship 1#	Ship 2#	Ship 3#	Ship 4#	Ship 5#
Static optimization	Fuel consumption (t)	8.33	9.41	9.17	9.16	8.26
	CO_2 emissions (t)	26.71	30.16	29.41	29.37	26.47
	$EEOI_s$ [g/(t·n mile)]	12.68	11.38	13.15	10.09	9.98
Dynamic optimization	Fuel consumption (t)	8.19	9.22	9.07	9.03	8.10
	CO_2 emissions (t)	26.26	29.55	29.07	28.95	25.96
	$EEOI_s$ [g/(t·n mile)]	12.46	11.15	13.00	9.95	9.79
Reduced percent (%)		1.69	2.03	1.13	1.42	1.93

Table 7
A comparison between the optimization results of the fleet energy consumption.

Item	Traditional operation decision-making method	Bi-level dynamic optimization method	Reduced percent (%)
Total fuel consumption (t)	46.80	43.61	6.82
Total CO_2 emissions (t)	150.03	139.80	6.82
$EEOI_f$ [g/(t·n mile)]	11.95	11.14	6.82

5.2.2. Lower-level dynamic optimization result of fleet energy consumption

The operation time for each ship, obtained from the upper-level optimization, is used as the time constraint for the dynamic optimization of the lower-level fleet energy consumption, as shown in Table 4. In addition, other parameters required for dynamic optimization of the fleet energy consumption in the lower level are showed in Table 5. By adopting the above model and solving method, we get the optimal results including the optimal sailing speeds and energy consumption. In addition, the $EEOI_s$ (energy efficiency operational index of single ship) for each ship can be obtained by Eq. (31), in which, C_{carbon} means CO_2 conversion rate of the fuel and it is 3.206 for the diesel oil (Burel et al., 2013).

$$EEOI = \frac{Q_{total} \cdot C_{carbon}}{W_{load} \cdot S} \tag{31}$$

The obtained optimal sailing speeds, energy consumption, and $EEOI_s$ of different ships by the bi-level dynamic optimization method are shown in Figs. 9–13. In addition, in order to demonstrate the validity of the dynamic optimization method for fleet energy consumption, we also obtain the optimization results in terms of the speeds, fuel consumption and $EEOI_s$ for each ship at different steps by the static method, as shown in Figs. 9–13. The static optimization in this paper means that it does not consider the time-varying environment at different time steps, and assumed that the environment at the same location is unchanged over the time. Therefore, the optimization process for a whole voyage before starting the voyage is only carried out once.

5.3. Results analysis and discussion

5.3.1. Comparative analysis

As can be seen from Figs. 9–13, the optimized speeds at each time step are different due to the differences in the navigational environment and port operation time. The time-varying environment and port operation time can add to the optimization potentials for the fleet energy consumption. In addition, the energy consumption, CO_2 emissions and $EEOI_s$ for each ship adopting the dynamic and static optimization methods are shown in Table 6. Among others, the CO_2 emission is obtained by:

$$M_{CO_2} = Q_{total} \cdot C_{carbon} \tag{32}$$

By comparing the data in this table, we can see that the dynamic optimization can further improve the fleet energy efficiency than the static method that does not consider the time-varying environment. The maximum reduction is 2.03% (2# ship) and the minimum reduction is 1.13% (3# ship). What's more, we can reduce the energy consumption of the 1#, 4# and 5# ships by 1.69%, 1.42% and 1.93% respectively. Therefore, the proposed dynamic optimization method of fleet energy consumption can help to effectively abate the fuel consumption and CO_2 emissions, and thus improve the fleet energy efficiency.

In addition, the proposed dynamic optimization method considers the time-varying environment and external factors, making it can reflect the actual situation and have more accurate optimization results than the static optimization method. Therefore, it can be concluded that the larger the change in the environment with time, the more the result of the static optimization deviates from the optimal value, and the dynamic optimization method will have a better optimization effect than the

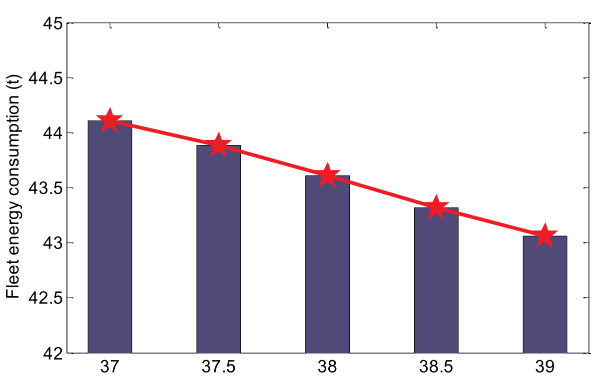

Fig. 14. The fleet's energy consumption under different total fleet operational time.

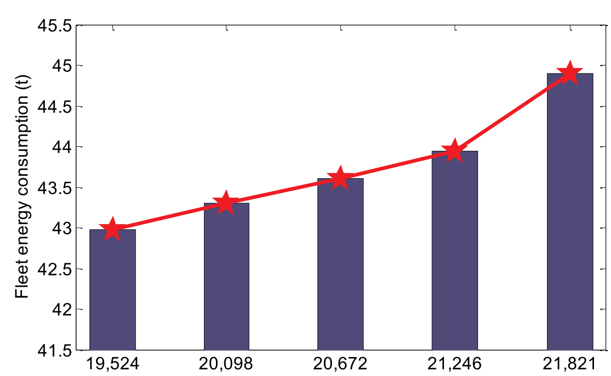

Fig. 15. The fleet's energy consumption under different total cargo mass of the fleet.

Table 8
The statistics of the sensitivity analysis at different levels.

Levels	Fleet's operational time/d	Fleet's fuel consumption/t	Sensitivity value	Fleet's cargo mass/t	Fleet's fuel consumption/t	Sensitivity value
1	37	44.11	0.392	19524	42.98	0.268
2	37.5	43.88	0.481	20098	43.31	0.246
3	38	43.61	–	20672	43.61	–
4	38.5	43.32	0.504	21246	43.94	0.278
5	39	43.06	0.450	21821	44.90	0.794

static optimization method. From the optimization results, we can see that for the 2# ship, the largest differences occur between the dynamic optimization speed and the static optimization speed due to the time-varying navigational environment. Therefore, it has the largest optimization percent of energy consumption compared with other ships. On the contrary, for the 3# ship, the least differences are found between the dynamic optimization speed and the static optimization speed. The optimization results show that it has lowest optimization percent of energy consumption compared with other ships.

5.3.2. Analysis of the optimization results of the fleet energy consumption

The total energy consumption, CO_2 emissions and $EEOI_f$ (energy efficiency operational index of ship fleet) by adopting the traditional operational decision-making method (the only upper-level optimization method for the fleet operational decision-making. It means that the influence of the environmental conditions on fleet's fuel consumption is not considered and the speed optimization under different environmental conditions is not carried out.), and the bi-level dynamic optimization method are illustrated in Table 7. The bi-level dynamic optimization could further reduce the total energy consumption and emissions by about 6.82% than the traditional fleet operational decision-making method. Therefore, the bi-level distributed dynamic optimization can improve the energy efficiency of the fleet effectively.

5.4. Sensitivity analysis

In order to analyze the effects of various parameters on the fleet's energy consumption and to identify the robustness and effectiveness of the optimization results, a sensitivity analysis of the fleet's energy consumption under different total fleet's operational time and different total cargo mass of the fleet is carried out. Sensitivity analysis is to study how the uncertainties of a mathematical model or system output are affected by the uncertainties of the different input sources. The sensitivity analysis of output results under different inputs can contribute to know the influence of the variables on the outputs. For models with multi-input variables, sensitivity analysis is an important part of model building and its quality (Wang et al., 2017a).

Before the sensitivity analysis, the fleet's energy consumption under different total fleet operational time and different total fleet's cargo mass is analyzed and the results are shown in Figs. 14 and 15, respectively. As can be seen from Fig. 14, a longer fleet operational time will result in lower energy consumption, which is due to the greater optimization potential for ships to slow down for a longer operational period. However, the longer operational time will fail to meet the transport demands within the specified time. In addition, as can be seen from Fig. 15, the fleet's energy consumption increases with the increase of the fleet's cargo mass. This is because the increase of the cargo mass increases the ship's draft and thus increases its resistance.

For the sensitivity analysis method in this paper, the benchmark of total fleet operational time is 38 d and the benchmark of the total cargo mass of the fleet is 20672 t, and each factor is divided into five levels. The fleet's energy consumption under different conditions and the sensitivity values of each level that are obtained are shown in Table 8.

Based on the statistics of the sensitivity analysis at different levels, the calculated sensitivity discriminant coefficient of the fleet's operational time and cargo mass is about 0.46 and 0.40, respectively. As can be seen, the sensitivity discriminant coefficient of the fleet's operational time is larger than the fleet's cargo mass. Therefore, it can be concluded that the voyage's operational time has a more significant influence on the fleet's energy consumption than the fleet's cargo mass, and the fleet's energy efficiency can be improved by prolonging the voyage's operational time.

6. Conclusions and discussions

Considering the uncertainty of the fleet operational conditions and the multitude of influencing factors, a dynamic optimization method is proposed for the fleet energy consumption. A bi-level optimization model, including an upper-level operational decision-making model and a lower-level distributed navigation optimization model, is established, to improve economy and reduce energy consumption of the fleet. The DMPC-based dynamic optimization is investigated for the decisions on the optimal speeds under the updated weather conditions and port operation information. Based on the designed dynamic optimization algorithm, we developed the DOFEC controller, which can compensate for disturbances resulting from the constantly changing environments and port operation information during the entire voyage. The case study shows that we can obtain better fleet energy efficiency using the proposed method by considering a multiple of time-varying influencing factors. We find that this proposed bi-level distributed energy consumption dynamic optimization method can reduce the total energy consumption and emissions of the fleet effectively. Compared with the method that does not consider the time-varying environment, we can further reduce the energy consumption of each ship by at least 1.1%. From the perspective of system-level fleet energy consumption, we can reduce the energy consumption by as much as 6.8%. It means that about 3.2 tons fuel could be saved for a single eight-day voyage. It is undoubtedly a good benefit for the shipping corporations. In addition, from the sensitivity analysis, we find the proposed dynamic optimization method can obtain the optimization results under different conditions, and the voyage operational time has a more significant influence on the fleet's energy consumption than the fleet's cargo mass.

The proposed bi-level dynamic method can also be extended to other kinds of ship fleet when the relevant information is available. It should be noted that there are differences in the operational modes for different ship fleets, e.g., service frequency requirements, transport modes. Therefore, an extension of this study to different kinds of operational modes and ship fleets would be our future study. With increasingly stringent emission regulations, shipping companies should explore novel effective methods to reduce energy consumption and CO_2 emissions. This paper proposed a novel dynamic optimization method based on the DMPC strategy. It can provide a new way for the fleet managers to improve economy and reduce CO_2 emissions by the system-level optimization of fleet energy consumption.

Author contributions section

Kai Wang: Conceptualization, Methodology, Software, Validation, Funding acquisition and Writing - Review & Editing;

Jiayuan Li: Investigation, Writing-Original draft preparation, Validation and Visualization;

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Supervision;

Lianzhong Huang: Methodology, Validation, Supervision and Project administration;

Xiaoli Jiang: Methodology, Investigation, Writing - Review & Editing;

Yupeng Yuan: Methodology, Validation, Writing - Review & Editing;

Ranqi Ma: Methodology, Investigation, Writing - Review & Editing;

Rudy R. Negenborn: 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.

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