Research on Multi-interval Coupling Optimization of Vessel Speed for Energy Efficiency

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Abstract

By taking the YUKUN ship as the research object, this research aims to improve the energy-saving effect of the YUKUN ship. Through speed optimization, the value of the energy efficiency operation index (EEOI) is minimized. The effects of uncertainty factors and their mutual coupling on EEOI in the process of ship operation are analyzed. To obtain the design variables (ship speed) in the optimized design, the speed data of the round-trip voyage between the Dalian and Haiyang Islands are taken as the source data. The design space of the design variables is obtained using data analysis methods, such as time equidistantization of speed data, acquisition of stationary segment, data expansion based on cloud model theory and normal test hypothesis. The adaptive simulated annealing algorithm (ASA) is then used for deterministic optimization. 6σ analysis is used to analyze the reliability of the optimal solution, and 6σ optimization improves its reliability. The relationship between the uncertain factors (i.e. flow velocity [*Vw*], ship wet surface area [*S*], ship cargo loading rate [*R*]) and EEOI is examined. The interval analysis method is used to embed the uncertain factors into the double-layer nested optimization system to explore the effect of single uncertain factor and the coupling effect of multiple uncertain factors on EEOI. The results show that *Vw* and *S* can improve the energy-saving effect of EEOI, *R* significantly decreases the energy-saving effect of EEOI, and the coupling effect of multiple uncertain factors inhibits EEOI. This research is of great significance to energy conservation, emission reduction and reduction of operating costs in the process of ship operation.

Keywords: EEOI; Data analysis; Uncertainty; Interval analysis method; Coupling effect

0 Introduction

With the continuous emission of greenhouse gas, the global climate is gradually warming. In the Fourth Greenhouse Gas Report in 2020, global maritime greenhouse gas emissions increased by 9.6% from 2012 to 2018. By 2050, global CO_2 emissions are estimated to reach 90%–130% that of 2008. In this report, four typical indicators are used for carbon intensity assessment: energy efficiency operational indicator (EEOI), annual efficiency ratio (AER), CO_2 emissions per distance travelled (DIST) and CO_2 emissions per hour underway (TIME). EEOI has reasonable economic significance and can objectively reflect the effect of various factors on the carbon intensity of operations[1]. EEOI is a non-mandatory measure that represents the amount of CO_2 emissions generated by per unit distance travelled per unit passenger and cargo during ship operation[2].

In the process of ship operation, energy saving, emission reduction and reduction of operating costs are crucial to gain speed. Wang[3], Huang[4] and Li[5] applied different optimization algorithms to ship speed optimization to obtain the optimal speed of ship navigation, which can effectively reduce fuel consumption of the ship's main engine and achieve energy saving and emission reduction. Lindstad[6] et al. found that speed optimization could reduce the emission rate of ship pollution gas by about 19% without increasing operating costs. Gao[7] et al. used the energy saving and emission reduction of ships as the data mining goal and adopted the dichotomous K-means clustering method to cluster the data of various working conditions through a statistical distribution map and a Gaussian mixture model to obtain the power–fuel consumption per nautical mile relationship curve. Liu[8] et al. constructed a back propagation neural network model with actual ship instance data and obtained the expected curve of the main engine power and speed through data cleaning, mining and analysis to evaluate fuel consumption. Zhang[9] et al. developed a speed data-driven model based on neural network theory to predict the energy efficiency of Arctic ships and obtain the best energy efficiency route. Wang[10] et al. used ship navigation data, weather data and ocean data to develop a new type of ship fuel consumption prediction model based on the LASSO regression method. The authors proved the superiority of this method over other methods for predicting fuel consumption. Bal Besikci[11] et al. develop a decision support system (DSS) employing ANN-based fuel prediction model for energy efficient ship operations. The performance of the ANN is compared with multiple regression analysis (MR), and its superiority is confirmed. Bal Besikci[12] et al. applied the Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) approach to prioritize the weight of each measure, and provided a strategic approach to identify energy efficient solutions to shows the relative importance of operational measures. The above mentioned studies describe the effect of speed on operational energy efficiency. Conversely, this research analyses the speed source data to obtain a range of design variables and prepare for the subsequent optimization design.

The deterministic optimal scheme is often close to the constraint boundary. If the design variables are uncertain, the optimization scheme has deviation, and the reliability of the optimization scheme is low. Hou[13] et al. quantitatively described the uncertainty level of 6σ theory and introduced it into an unmanned vehicle navigation performance optimization model to obtain a reasonable and high reliability optimization scheme. Li[14] et al. proposed a collaborative optimization based on laminated parameters and a 6σ design to obtain a composite pressure hull with high reliability, which could solve the problems of low efficiency and non-convergence of design variables in direct optimization. Based on 6σ theory, Mu[15] optimized the uncertainty of the water-drop Autonomous Underwater Vehicle (AUV). Compared to deterministic optimization, the reliability of the design variables and constraints was improved, although the resistance increased. Zheng[16] et al. improved PSO from four aspects， namely data processing of particle swarm population initialization, data processing of iterative optimization, particle velocity adjustment, and particle cross-boundary configuration, and optimized the hull form of an engineering vessel at Fn=0.24 to reduce the wave-making resistance coefficient under static constraints. Liang[17] et al. considered the uncertainty of ship type design and completed the optimal spacing configuration of an AUV based on 6σ theory. The above indicates that the 6σ method could improve the reliability of the scheme. To reduce the uncertainty of design variables, the present research combines the 6σ optimization method with EEOI to ensure that the output response has a high level of reliability and quality.

However, in the study of operational optimization, uncertain factors should be considered to ensure the feasibility and accuracy of the optimization scheme. Diez[19] et al. considered the uncertain factors of operation and environment and used the robust optimization method to minimize the mean and variance of transportation costs in the ship design stage. Cheng[19] et al. analyzed the uncertainty of input parameters and proposed a framework for uncertainty and sensitivity analysis based on artificial neural networks. The results were conducive to the optimization of data-driven motion models. Chen[19] et al. took inland ships as an example to avoid uncertainty in a theoretical model and developed the ship EEOI and main engine speed model to improve ship energy efficiency level. Moore[21] proposed the interval analysis method, which could avoid deviation caused by errors to a certain extent in the actual design analysis of engineering structures, and found it to have an application potential. Hou[22] et al. introduced the uncertainty of single-stage and multi-stage ice load and water speed into the interval optimization system in the ship speed optimization design process, analyzed its randomness and tested a series of cases. The optimized results showed that EEOI was reduced by about 15%. Wen[23] et al. established the interval uncertainty model of ship-borne photovoltaic power generation based on ship swing and used the interval analysis method to determine the optimal size of an energy storage system (ESS) in a hybrid ship power system, thus reducing fuel consumption, reducing ESS cost and controlling greenhouse gas emissions. Celik E[24] proposed a comprehensive multi-criteria decision method extended by interval-type two fuzzy sets (IT2FSs), which are used to select the appropriate ship loader type in maritime transportation. In the IT2FS environment, the analytic hierarchy process (AHP) and the technique for order preference by similarity to ideal solution (TOPSIS) are combined to overcome the uncertainty of judgment and expression in decision making and to include the hierarchy in the IT2FS environment. AHP and TOPSIS were found to overcome the uncertainty of judgment and expression in decision making. Wang[25] et al. constructed a double-layer nested optimization system based on the interval analysis method and discussed the relationship between the main dimensions and EEDI. So this research uses the interval number to obtain the uncertainty interval optimization problem based on the double-nested, and interval number conversion models to convert the uncertainty interval optimization problem into a deterministic multi-objective double-nested optimization problem. *Vw*, *S* and *R*, with low sensitivity of the objective function, are analyzed as uncertain factors, and the effect of the coupling between uncertain factors on the objective function is explored to reduce the inefficient problem caused by the double-nested optimization system.

This research takes the YUKUN ship as the research object and optimizes its energy efficiency design during ship operation. Data are analyzed to obtain the design variables and perform the EEOI deterministic optimization of speed. The uncertainty of speed is reduced through 6σ analysis and optimization. The uncertain double-layer nested optimization system is developed using the interval analysis method to research the effect of uncertain factors and their coupling effects on the energy-saving effect of EEOI.

1 EEOI numerical modelling

Ship EEOI is an international unified energy efficiency evaluation standard for ships in operation. It can assist shipowners, ship operators and relevant units and organizations to evaluate the CO_2 emission performance of their fleets during navigation operations. It is defined as the CO_2 emission value of the unit transport turnover of the ship, which is the most representative indicator of the ship operating energy efficiency. EEOI formula for a single voyage is as follows[26]:

$$EEOI = \frac{\sum_j FC_j \times C_{Fj}}{m_{cargo} \times D} \tag{1}$$

where: j is the type of fuel, FC_j is the total amount of fuel consumed by the ship during the operation, C_{Fj} is the CO_2 emission factor, m_{cargo} is the actual cargo capacity, D is the actual distance travelled by the ship during operation.

EEOI values are different with different cargo capacities on the same voyage. In order to facilitate the calculation, the ship cargo loading rate (R) is introduced. This parameter reflects the ship type characteristics of the ship and directly reflects the operating conditions of the shipping company, which has high economic sensitivity.

$$R = \frac{m_{cargo}}{DWT} \tag{2}$$

The total fuel consumption FC of single voyage can be divided into the fuel consumption of main engine, auxiliary engine and boiler. The formula can be rewritten as follows:

$$EEOI = \frac{\sum_j (FC_{ME} \times C_{FME} + FC_{AE} \times C_{FAE} + FC_{BE} \times C_{FBE})}{R \times DWT \times D} \tag{3}$$

$$\begin{aligned} FC_{ME} &= Q_{ME} \times T_i \\ FC_{AE} &= Q_{AE} \times T_T \\ FC_{BE} &= Q_{BE} \times T_T \end{aligned} \tag{4}$$

where: Q_{ME} is main engine fuel consumption per unit time, Q_{AE} is auxiliary engine fuel consumption per unit time, Q_{BE} is boiler consumption per unit time, T_i is ship sailing time, T_T is total voyage time (the sum of running time and detention time).

Main engine fuel consumption can be expressed as:

$$\begin{aligned} Q_{ME} &= P_S \times SFC_{ME} = \frac{P_E}{P.C} \times SFC_{ME} = \frac{Rv}{75P.C} \times SFC_{ME} \\ &= \frac{1/2\rho SC_t v^2 v}{75P.C} \times SFC_{ME} = \frac{\rho SC_t v^3 SFC_{ME}}{150P.C} \end{aligned} \tag{5}$$

where: P_S is machine power, SFC_{ME} is fuel consumption rate of main engine; $P.C$ is propulsion coefficient; R_v is the work consumed by resistance R in unit time; ρ is the seawater density; C_t is the ship total resistance coefficient; S is the ship wet surface area; v is the speed through water.

Auxiliary engine fuel consumption can be expressed as:

$$Q_{AE} = P_{AE} \times SFC_{AE} \tag{6}$$

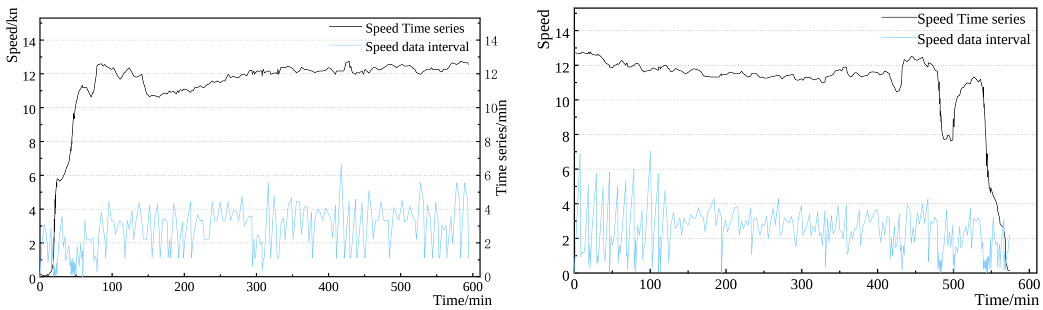
It assumes that fuel consumption per unit time of the boiler is fixed.

2 Acquisition of design variables

Navigation at reduced speed is considered a good measure of energy saving and emission reduction in ship operation, and it has been widely used by shipping companies. Machine power is transmitted to the propeller through a deceleration device, thrust bearing and the main shaft. Water pushes the propeller forward, and the ship sails forward at a certain speed. When speed is too high, the power required to propel the ship is greater, and fuel consumption is significantly increased. Navigation at reduced speed is an effective measure for a single ship to improve energy efficiency and reduce ship emissions[27]. Therefore, this research conducts a reasonable optimization of speed. On the premise of ensuring the safety of ship navigation, it not only meets the requirements of the arrival time of the ship, but it also minimizes the fuel consumption required for voyages. This is the main goal of the EEOI speed optimization of ships. Fig.1 is the trajectory map of YUNKUN ship round Dalian to and from Haiyang Island.

Fig. 1 Trajectory map of YUNKUN ship round Dalian to and from Haiyang Island

This voyage is the navigation trajectory map of the YUKUN ship for maritime practice, which is divided into two sections: one section starts from Dalian and ends at Haiyang Island, and the other section starts from Haiyang Island and ends at Dalian. The time of the two voyages is not continuous, resulting in the ship drifting, so the arrival point and starting point of the ocean island deviate. The source data of water speed from YUKUN ship's Speed Log are shown in Fig. 2.



(a)Dalian to Haiyang Island (b)Haiyang Island to Dalian

Fig. 2 The source data of water speed of YUKUN

2.1 Time Equidistantization of Speed

Due to the unequal interval of the obtained speed data time, the Lagrange quadratic interpolation method is used in MATLAB to conduct time equidistantization of speed. It starts from 0 with a 2-min interval for the time equidistantization of speed.

Lagrangian quadratic interpolation polynomial:

$$P = y^{k-1}L^{k-1}(x) + y^{k}L^{k}(x) + y^{k+1}L^{k+1}(x) \quad (7)$$

Interpolation basis function:

$$L_k = \frac{x - x_{k+1}}{x_k - x_{k+1}} \quad (8)$$

where: P is desired speed data, y is speed data, and x is time.

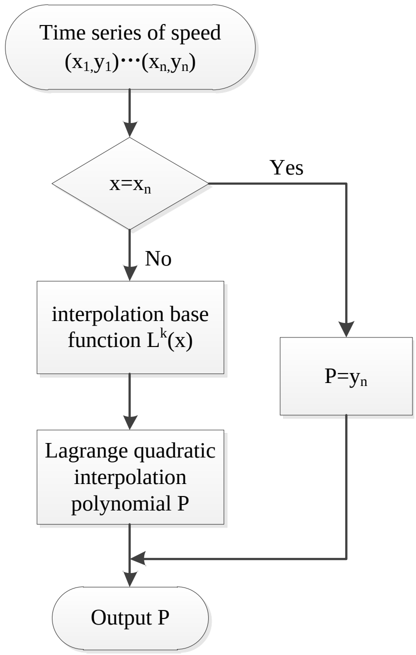
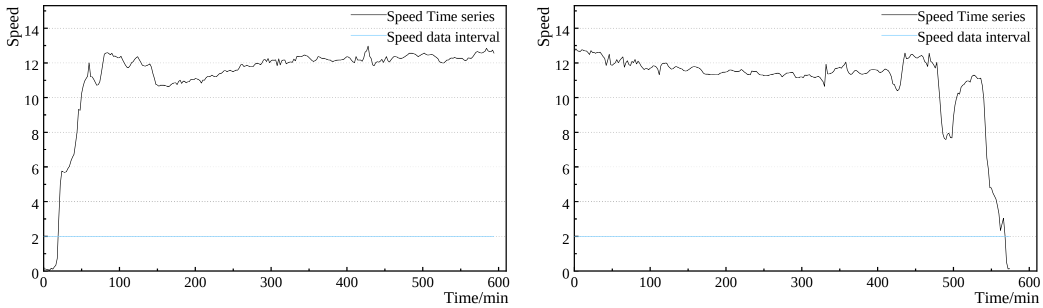


Fig. 3 Lagrange quadratic interpolation flow chart

In the case of known speed source data and the corresponding time, the time series of speed is obtained: $(x_1,y_1),(x_2,y_2)\cdots(x_n,y_n)$. If $x=x_n$, the corresponding speed P is obtained directly. Otherwise, according to the principle of proximity, two sets of data $(x_1,y_1),(x_2,y_2)\cdots(x_n,y_n)$ similar to x_k. are selected. According to the interpolation basis function $L^k(x)$, the Lagrangian quadratic interpolation polynomial P is obtained. Then, the time series of speed at equal intervals P is summarized. Fig. 4 shows the speed data at time equidistantization. Compared to the initial data, the interval of speed data processed by time equidistantiation becomes 2 min, which is no longer disorderly. The changing trends of the two sets are the same, but the latter has higher data accuracy, is easy to use and is easy for conducting follow-up research.

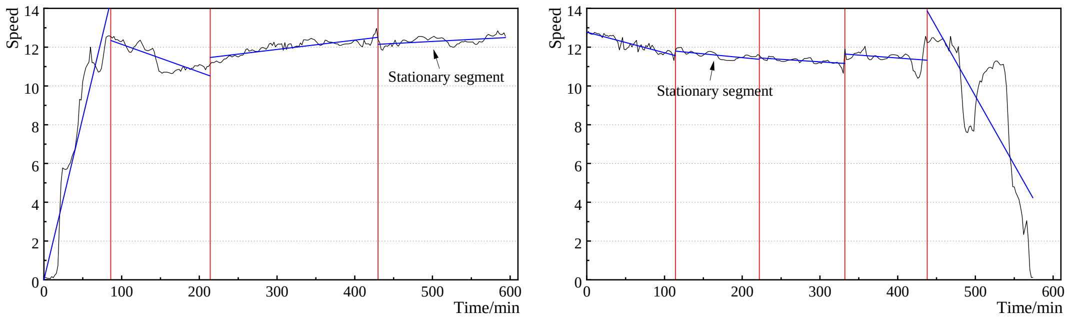


(a)Dalian to Haiyang Island (b)Haiyang Island to Dalian

Fig. 4 The speed data after time equidistantization

2.2 Acquisition of stationary segments

The design space of design variables should be stable so that the speed time series could continue along the existing shape inertia. That is, the speed time series for a certain period in the future is approximately consistent with the current speed time series. Therefore, only the time series based on the stationary segment is effective[28]. In this research, the *Findpeaks* function in MATLAB is used to intelligently segment the maximum and minimum values of speed data. The time-equidistant speed data are imported into the *Findpeaks* function. As the *Findpeaks* function is used to find the local peak in the data, the minimum interval of the data is adjusted to 100. The wave peak and trough are marked in an interval, that is, the corresponding maximum and minimum values. Extreme points are taken as the piecewise bounds, and linear fitting is performed. The result is shown in Fig. 5:



(a)Dalian to Haiyang Island (b)Haiyang Island to Dalian

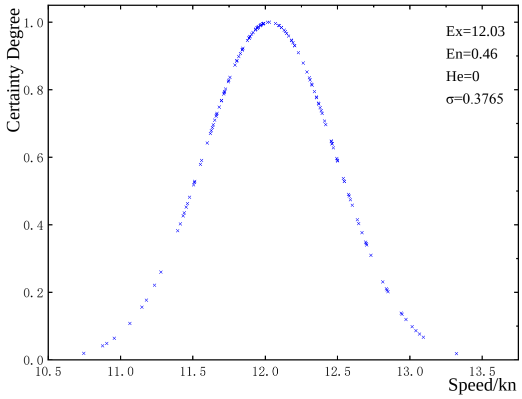
Fig. 5 Intelligent segmentation and linear fitting of time series of speed

In Fig. 5, the black line is the speed data, the red line is the intelligent piecewise line, and the blue line is the linear fitting line. In the linear fitting region, the minimum slope is the stationary segment. The stationary segment of Dalian to Haiyang Island is 432-596 min, the stationary segment of Haiyang Island to Dalian is 114-224 min. Due to the small amount of speed data in the stationary segment, the cloud model theory is used to expand the data.

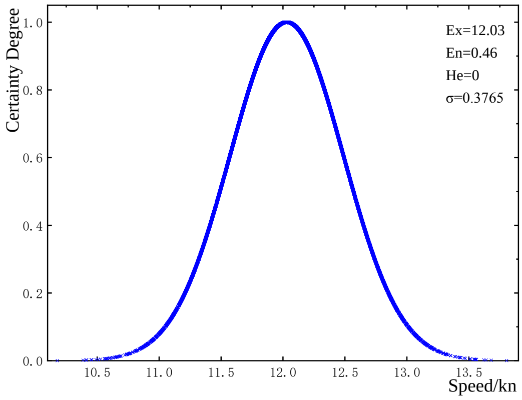
2.3 Data expansion based on cloud model theory

Based on statistical mathematics and fuzzy mathematics, cloud model theory combines forward cloud generator with reverse cloud generator and qualitative analysis with quantitative calculation, and deals with the uncertainty of the attributes of randomness and fuzziness[29]. Moreover, cloud model theory is a research hotspot of spatial data mining[30]. It draws on the advantages of natural language. It considers randomness and fuzziness in spatial data mining and integrates the two. It conducts a mapping between qualitative and quantitative[31]. Zheng[32] et al. investigated a dynamic space reduction optimization framework (DSROF), data mining is continuously performed during the optimization process to dynamically reduce the range and number of variables. The results indicate that the calculation cost in hull form optimization is reduced by 23 %.

The stationary segment is summarized, and the reverse cloud generator is used to accurately describe the three digital characteristics(i.e. expectation [*Ex*], entropy [*En*] and hyper-entropy [*He*]) to obtain (Ex,En,He)=(12.03,0.46,0). The forward cloud generator is then used to expand insufficient data, and the expansion multiple is set to 100. As shown in Fig. 6, the expanded data volume is complete and abundant.



(a)Before expansion



(b)After expansion

Fig. 6 Comparison of speed data before and after expansion based on cloud model theory

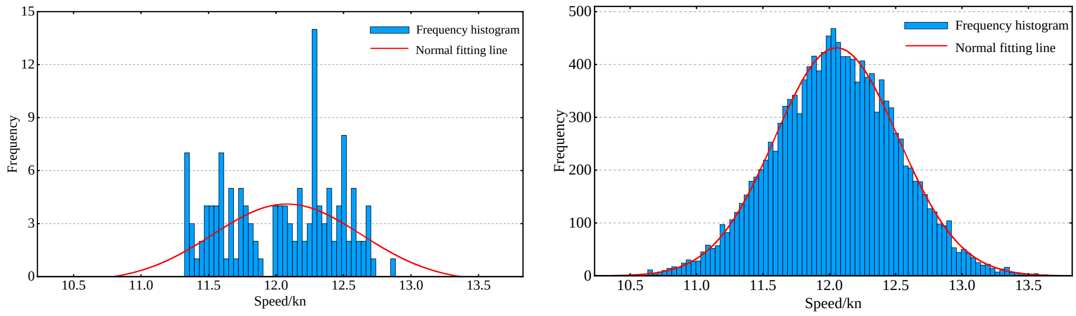
The mathematical characteristics after expansion are shown in Tab. 1. The standard deviation of the expanded data is 0.4623, which is greater than 0.4162 before expansion. However, the standard error is greatly reduced, the randomness of the data is reduced, and the data are more convincing and realistic.

Tab. 1 The mathematical characteristics

	Stationary segment	Data expansion
Mean value	12.02986	12.03164
Standard error	0.035433	0.003936
Median	12.11451	12.03193
standard deviation	0.416248	0.462323
Variance	0.173263	0.213742
Kurtosis	-1.23456	-0.03203
Skewness	-0.19604	-0.02312
Minimum	11.3137	10.21413
Maximum	12.84199	13.81152

2.4 Normal test hypothesis

In the traditional signal processing process, signal and noise are assumed to conform to normal distribution. However, based on in-depth research, the normal assumption has been found to be unreasonable. The signal system designed based on the normal assumption will have performance degradation under non-normal conditions. Therefore, a normality test should be carried out when analyzing sample data[33].



(a)Stationary segment (b)Data expansion

Fig. 7 Frequency histogram

Fig. 7 is the frequency histogram, where Fig. 7-(b) is more consistent with the normal fitting line. From the perspective of descriptive statistical methods, whether the data obey a normal distribution should be tested[34]. The *Normplot* function is used to evaluate the normality of data. The sample data points are concentrated near the red reference line, indicating that the sample data obey a normal distribution approximately (Fig. 8).

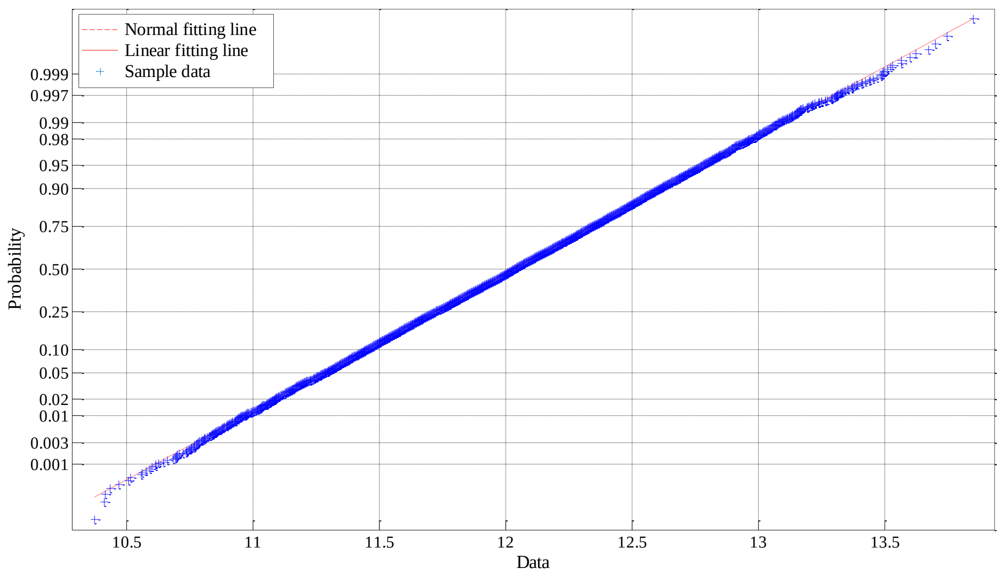


Fig. 8 Normal probability diagram

3 Deterministic optimization

Optimization problems in engineering are often complex. The objective function may have multi-peak, nonlinear, discontinuous and non-differentiable functions.

Design variables and constraint functions can be linear, nonlinear, continuous or discrete variable sets. In the process of optimization design, the optimization design problem is solved as a deterministic problem without considering the objective design uncertainty. The deterministic optimization design problem model is:

$$\begin{cases} \min\limits_{x} f(x) \\ s.t \quad g_j(x) \geq 0 \quad j = 1, 2, \ldots, n \\ x \in [x^L, x^U] \end{cases} \tag{9}$$

where: x is the design variable; *f(x)* is the objective function; *g(x)* is the constraint function; x^L, x^U is the upper and lower limits of the design variables.

3.1 EEOI deterministic optimization

In this research, the adaptive simulated annealing optimization algorithm (ASA) is used to explore the global results. One advantage of ASA is that it decreases the number of samples for large-scale combinatorial optimization problems[25]. In this research, the YUKUN ship is taken as the research object, the design variable is the ship speed, and $\mu\pm3\sigma$, in the stationary segment of speed, is taken as the design space. Other indicators are deterministic indicators, and the EEOI deterministic optimization scheme is established. The YUNKUN ship parameters and deterministic optimization models are shown in Tab. 2 and Tab. 3.

Tab. 2 The YUKUN ship parameters

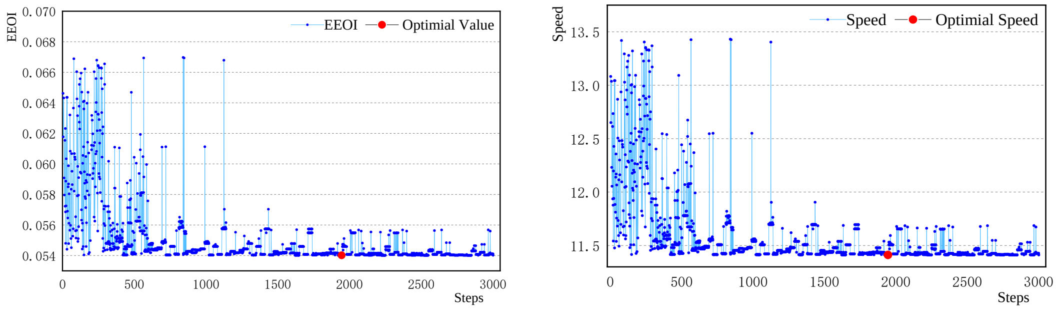
The main parameters	Units	Numerical value
Overall length	L_{oa}/m	116
Design waterline length	L_{WL}/m	106.5
Length between perpendiculars	L_{pp}/m	105
Moulded beam	B/m	18
Moulded depth	D/m	8.35
Design draft	d/m	5.4
Block coefficient	C_b	0.5596
Carrying capacity	DW/t	2256.7
Displacement volume	∇/m^3	5735.5
Full load displacement	Δ/t	5878.8
Height of center of gravity	KG/m	6.45
Initial metacentric height	h/m	1.71

Tab. 3 EEOI deterministic optimization model

Objective: ● Under ship operating conditions, Minimum EEOI
Design variable: ● Ship Speed: V_{ref}，kn，$V_{ref} \in [10.78, 13.28]$
Constraints: ● Estimated total voyage time: $T_T \leq 16.5h$;

● Estimated segmented voyage time: $T_1 \leq 8.58h$, $T_2 \leq 8.32h$; ● Ship speed between limit power speed and maximum design speed.
Global optimization: ● Adaptive Simulated Annealing Optimization Algorithm [ASA]; ● Maximum iterations: 3000; ● Other parameters default.

According to the parameters in Table 3, the following optimization curves are obtained:



(a)EEOI (b)Ship Speed

Fig. 9 Deterministic optimization curve

Fig. 9 presents the EEOI deterministic optimization curve obtained by 3000 iterations of the ASA. Fig. 9-(a) is EEDI change curve, and Fig. 9-(b) is ship speed change curve. In the initial stage, EEDI is explored in the global range with large fluctuations up and down. As the number of iterations gradually converges, tends to be converge. After stabilization, EEOI value by around 0.054, and the speed value by around 11.5. Finally, the optimal solution is found in step 1945.

3.2 6σ Analysis and Optimization

Deterministic analysis is commonly used in optimization design. The design variables are defined by deterministic indicators. However, in the optimization design, the constraints of the deterministic optimal solution are close to the boundary. Design variables are uncertain, which leads to errors in the objective function. Therefore, the deterministic optimization design has certain defects. Reliability analysis of deterministic optimization can reduce the effect of uncertainty on design variables.

The design scheme that meets the 6σ level corresponds to a reliability of 99.9999998%. Therefore, 6σ analysis is adopted for reliability analysis, and it uses the mean value reliability method (Fig. 10). At an average value μ_x of the random variable, the Taylor series expansion is carried out using the failure function $g(x)$. The failure rate can be calculated according to $P_f = (-\beta)$, where $\beta = \mu_g / \sigma_g$. The mean value reliability method based on the first-order Taylor expansion is the most effective reliability analysis method in *Isight* numerical evaluation and reliability calculation[35]. The first order approximate formula for calculating the mean value and standard deviation of product performance *Y*:

$$\mu_y = Y(\mu_z)$$
$$\sigma_y = \sqrt{\sum_{i=1}^{m} \left(\frac{\partial Y}{\partial z_i}\right)^2 (\sigma z_i)^2} \tag{10}$$

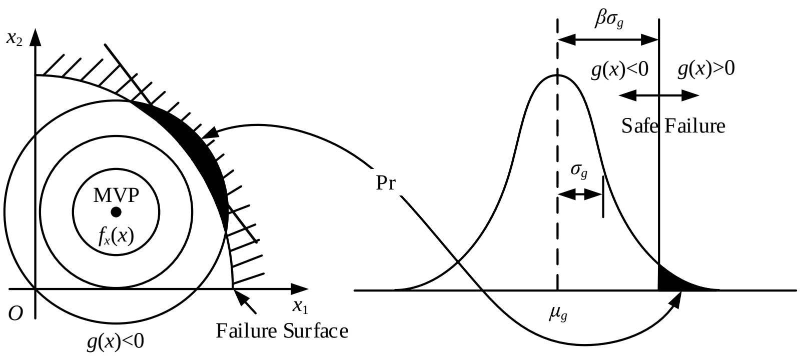


Fig. 10 Mean value method reliability analysis method

The 6σ optimization principle is shown in Fig. 11. To find a ‘flat’ region in the design space, the output response fluctuation caused by uncertainty is minimized, and the reliability probability of the constraint requirements is met, thus improving the reliability of the objective function.

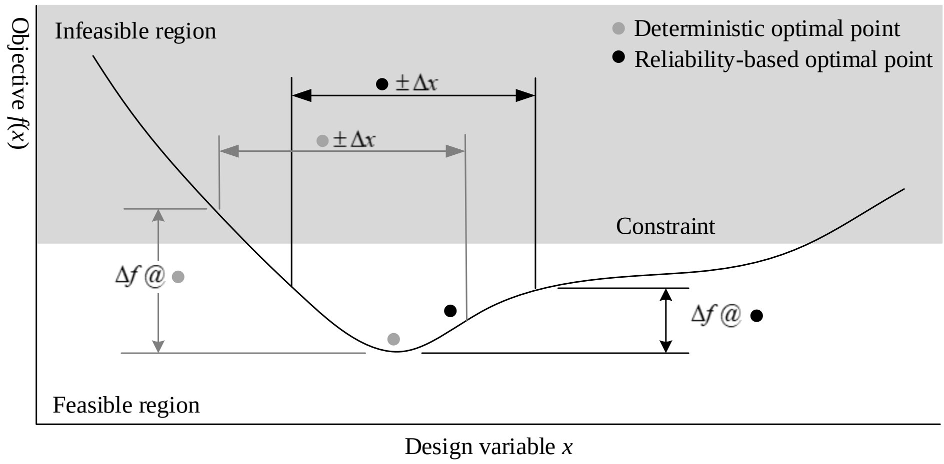


Fig. 11 6σ Optimization Principle

6σ optimization as shown in tab. 5:

Tab. 5 Comparison of 6σ optimization results

Output response	Deterministic optimization		6σ optimization	
	Deterministic optimization solution	6σ analysis	Quality optimization solution	Quality level
Total voyage time: T_T	16.89	1.1079σ Reliability=73.21%	15.82	7.6056σ Reliability=100%
Dalian to Haiyang Island voyage Time: T_1	8.57	0.2328σ Reliability=18.41%	8.03	6.0066σ Reliability=99.99%
Haiyang Island to Dalian voyage Time: T_2	8.31	2.4461σ Reliability=98.55%	7.79	8σ Reliability=100%
Speed constraint: V	11.31	8σ Reliability=100%	12.07	8σ Reliability=100%
Design variable: speed V_{ref}	11.31		12.07	
Objective function: EEOI	0.05402		0.05811	

It can be seen from Tab. 5 that in the deterministic optimization scheme. To achieve the optimal objective function. Among speed constraint reaches 8σ and reliability is 100%, while other constraints are close to boundary, reliability and quality level are low, and the reliability of optimization scheme is low. Although speed increases after 6σ optimization, it meets the 6σ quality level. The other output responses meet the 6σ requirements, and reliability is guaranteed. Therefore, the 6σ optimization scheme is used for the following uncertainty interval optimization comparison.

4 Uncertainty interval optimization

4.1 Interval analysis method

In the study of ship energy efficiency, the analysis methods that deal with uncertain factors are mainly probability method, fuzzy method and interval analysis method. The probability method considers structural parameters as random variables, and the joint probability density function of uncertain structural parameters is known. When there is no large amount of data to verify the correctness of the probability density, ensuring calculation accuracy is difficult. The fuzzy method is described by the membership function of known uncertain variables. However, the selection of the membership function of uncertain variables is subjective, which may cause artificial errors. The interval analysis method considers uncertain variables as ‘unknown but bounded’ variables under the condition of insufficient information. Through interval representation, it reduces the required sample information to a certain extent and has the advantages of high precision and a small amount of calculation. It is more consistent with objective reality and has been increasingly applied to the optimization design of ships.

The interval is a bounded closed set of real numbers, which can be expressed as[36]:

$$A^I = [A^L, A^U] = \{X \mid A^L \le X \le A^U, X \in R\} \tag{11}$$

where: the superscript *I*, *L*, *U* represents the interval, the lower bound of the interval, and the upper bound of the interval respectively. If and only if $A^L = A^U$, the interval is a real number.

It can also be described as:

$$A^I = (A^m, A^w) = \{X \mid A^m - A^w \le X \le A^m + A^w\} \tag{12}$$

where: *m* is the midpoint of the interval, and *w* is the radius of the interval.

Using interval analysis method to analyze uncertain factors, the uncertainty interval optimization problem can be expressed as:

$$\begin{aligned}
&\min f(x, p) \\
&s.t.\ \ g_j(x, p) \le b_j^I \\
&b_j^I = [b_j^L, b_j^U],\ \ j = 1, 2, \cdots, l, x \in \Omega^n \\
&p_i \in p_i^I = [p_i^L, p_i^U],\ i = 1, 2, \cdots, q
\end{aligned} \tag{13}$$

where: *x* is the design variable, *p* is the uncertain variable, *f* and *g* is the objective function and the constraint function respectively, which are the nonlinear continuous functions of the design variables x and the uncertain variables p. p is a fluctuation range, for any x, the values of the objective function and the constraints all constitute an interval.

The core of interval optimization is to solve the upper and lower bounds of the objective function. The maximum and minimum values of the objective function are obtained in the range of uncertain factors. The interval analysis method is used to fully consider the effect of uncertain factors to ensure the effective feasibility of the optimization scheme. Considering the uncertainty of design parameters, the uncertainty interval optimization model is shown:

$$\begin{aligned}
&\min \left\langle f_i^m(x,p), f_i^w(x,p) \right\rangle \\
&f_i^m(x,p) = \frac{f_i^L(x) + f_i^U(x)}{2} \\
&f_i^w(x,p) = \frac{f_i^U(x) - f_i^L(x)}{2} \\
&f_i^L(x) = \min\ f_i(x,p) \\
&f_i^U(x) = \max\ f_i(x,p) \\
&s.t. \quad P_x\left\{ g(x,p) \ge 0 \right\} \ge R_g \\
&\qquad\ \ P_x\left\{ h(x,p) \le \varepsilon \right\} \ge R_h \\
&x_{\min} + \Delta x \le \mu_x \le x_{\max} - \Delta x
\end{aligned} \tag{14}$$

where: $f^m(x,p)$ and $f^w(x,p)$ is the median and radius of the objective function in the uncertainty interval optimization; R_g is the constraint and R_h is the reliability; ε is the weighting factor, $\varepsilon \in [0,1]$; Δx is the tolerance of the design variables, $\Delta x > 0$; $P_x\{\ldots\}$ is the uncertainty measure of the constraints.

Tab. 6 is EEOI uncertainty interval optimization model, which is used to formulate the uncertainty interval optimization scheme.

Tab. 6 EEOI uncertainty interval optimization model

Objective:
● Under ship operating conditions, Minimum EEOI
Design variable:
● Ship Speed: V_{ref}, kn, $V_{ref} \in [10.78,13.28]$
Constraints:
● Estimated total voyage time: $T_T \le 16.5$h;
● Estimated segmented voyage time: $T_1 \le 8.58$h, $T_2 \le 8.32$h;
● Ship speed between limit power speed and maximum design speed.
Uncertainties:
● Flow velocity: *Vw*, Value: 2.80, Range: [2.52,3.08]
● Ship wet surface area: *S*, Value: 4000 Range: [3600,4400]
● Ship cargo loading rate: *R*, Value: 0.45 Range: [0.3,0.6]
Double-layer nested optimization system:
● Inner layer optimization: Adaptive simulated annealing optimization algorithm [ASA]; Maximum iterations: 200; Other parameters default.
● Outer layer optimization: Multi-Island genetic algorithm [MIGA]; Sub-Population size: 30; Number of Islands: 10;

	Number of generations: 10; Other parameters default.

4.2 Single Uncertain factor

The effect of single uncertain factors on the objective function is discussed, and the effect of flow velocity (*Vw*), ship wet surface area (*S*) and ship cargo loading rate (*R*) on EEOI is examined. The interval analysis method is used to embed the uncertain factors into a double-layer nested optimization system. Fig. 12 shows the flow chart of the double-layer nested optimization.

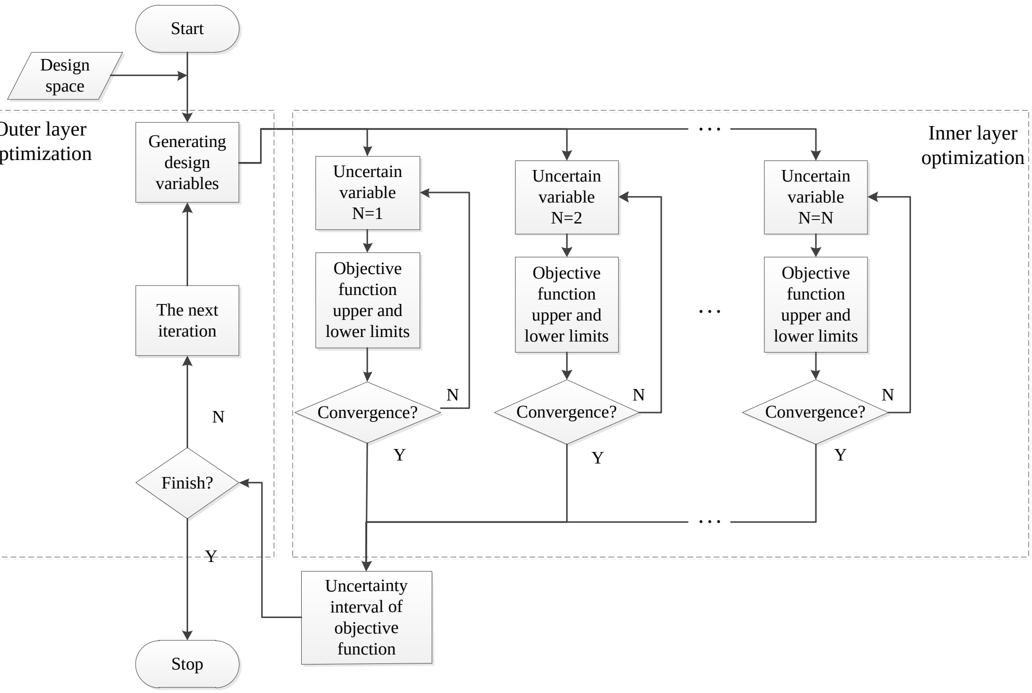
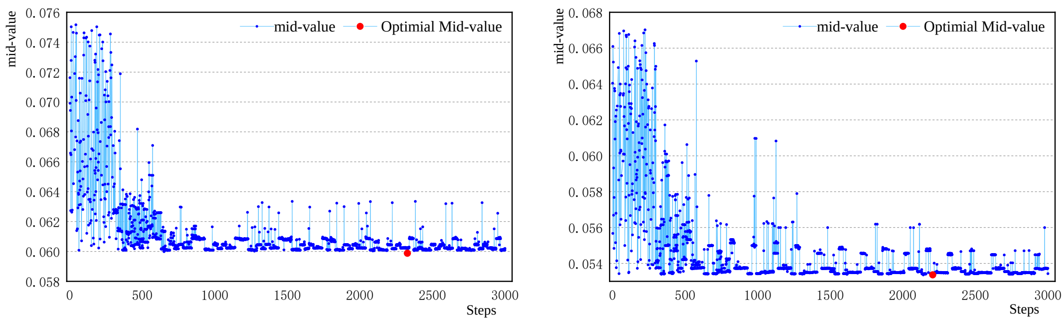
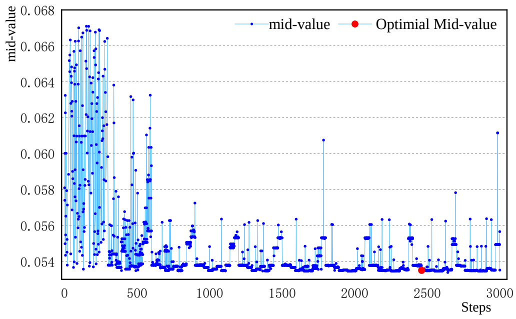


Fig. 12 Flow chart of multi-interval and double-layer nesting

The outer-layer optimization of the double-layer nested optimization system uses the multi-island genetic algorithm [MIGA], which has better global search capability and computational efficiency. Its sub-population size is set to 30, and the number of islands and generations is set to 10. Conversely, the inner-layer optimization uses the ASA, unlike in Wang[24]. ASA has better convergence and effectively explores global optimization solutions. Its maximum iteration is set to 200, and the other parameters are at default.



(a) Ship cargo loading rate: R (b) Ship wet surface area: S



(c) Flow velocity: Vw

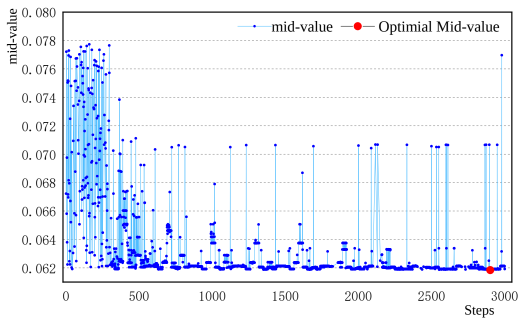
Fig. 13 Optimization curve of EEOI optimized by single uncertainty interval

Fig. 13 shows the initial stage of the optimization process. The fluctuation range of EEOI is large to achieve global optimization and avoid local optimization. The optimal lower limit is continuously determined to narrow the fluctuation range of EEOI until convergence. The effects of *S* and *Vw* on EEOI are similar, and the optimal is around 0.054. This is not significantly different from the deterministic optimization results, indicating that *S* and *Vw* have a small effect on EEOI. However, *Vw* finds the optimal at 2,462 iterations, and it takes a long time to achieve it. The optimal of EEOI with an uncertain factor *R* is 0.060, and the relative deterministic optimal fluctuates wildly, indicating that the uncertain factor *R* has a significant effect on EEOI.

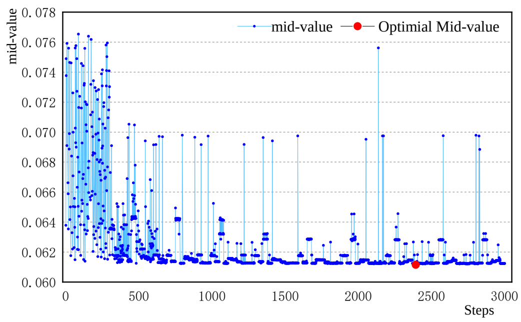
2#-4# in Tab. 7 is a single uncertain interval optimization scheme. It shows that uncertain factors *S* and *Vw* decrease the EEOI value, indicating that the existence of *S* and *Vw* promotes and enhances the energy-saving effect of EEOI. Among them, *Vw* decreases the EEOI value by 8.14%, and *S* decreases the EEOI value by 8.17%. The existence of uncertain factor *R* increases the EEOI value and inhibits its energy-saving effect, which increases the EEOI value by 3.03%.

4.3 Multiple uncertain factors

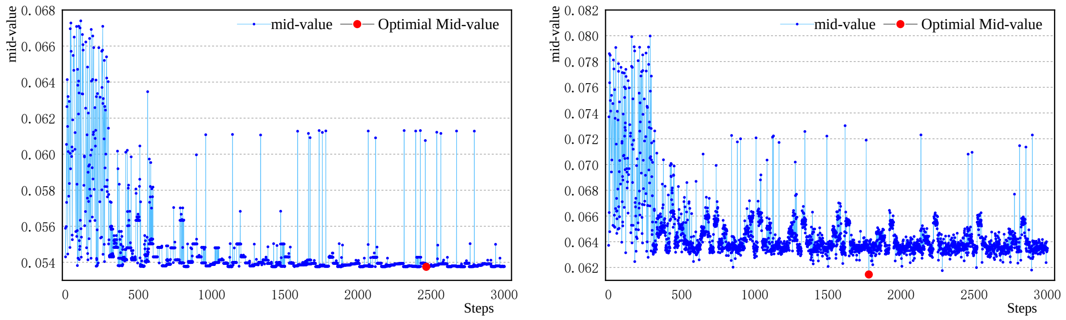
To further explore the effect of the number of uncertain factors and their coupling effects on EEOI, the effects of two uncertain factors or multiple uncertain factors and coupling effects on EEOI is analyzed.



(a) Uncertain factors *R*, *S*



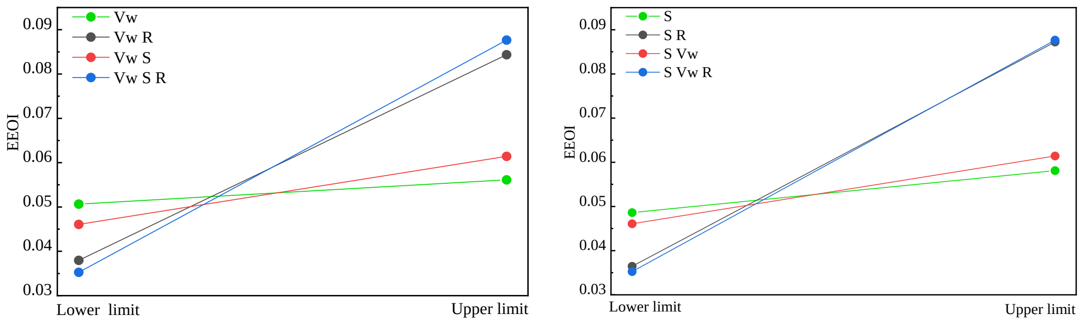
(b) Uncertain factors *R*, *Vw*



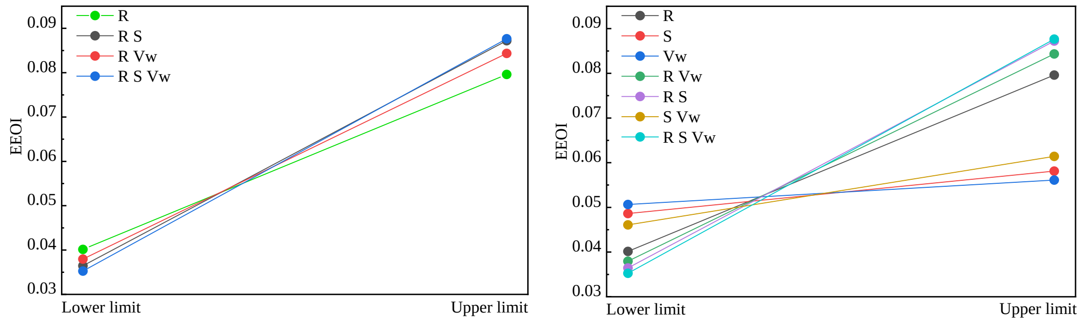
(c) Uncertain factors *S*, *Vw* (d) Uncertain factors *R*, *S*, *Vw*

Fig. 14 Optimization curve of EEOI under multiple uncertainties

Fig. 14 shows the optimization curves of EEOI under two uncertain factors and multiple uncertain factors, similar to the trend of the single uncertain factor optimization curve. However, the EEOI value of the optimization scheme with the uncertain factor *R* is relatively large, indicating that *R* has a significant correlation with EEOI. Moreover, when multiple uncertain factors exist simultaneously, the fluctuation range of the optimization curve is large, and the robustness is relatively poor.



(a)Add other uncertain factors under *Vw* (b)Add other uncertain factors under *S*



(c)Add other uncertain factors under *R* (d) EEOI range under *R*, *S*, *Vw*

Fig. 15 Optimal EEOI range under uncertainty

Fig. 15 shows Optimal EEOI range under uncertainty. Uncertain factors are added on the basis of single uncertainty factors; as the number of uncertainties increases, the radius of EEOI increases, and the robustness decreases. When there is an uncertain factor *R*, the range of EEOI increases significantly, indicating that *R* has the most significant effect on EEOI.

Tab. 7 Optimal scheme of uncertainty interval optimization

Case	Optimization method	V_{ref}	T_T	Uncertainties	Median and radius of EEOI	Relative 6σ optimization	σ level

				V_w	S	R		scheme/%	
1#	6σ	12.07	15.82	2.8	4000	0.45	EEOI=0.05811	0	-
2#	IO-Single	11.32	16.88	[2.52,3.08]	4000	0.45	m=0.05338 w=0.00273	-8.14%	1.166
3#	IO-Single	11.31	16.89	2.8	[3600,4400]	0.45	m=0.05336 w=0.00474	-8.17%	1.136
4#	IO-Single	11.33	16.87	2.8	4000	[0.3,0.6]	m=0.05987 w=0.01973	3.03%	1.241
5#	IO-Double	11.31	16.89	[2.52,3.08]	[3600,4400]	0.45	m=0.05375 w=0.00767	-7.50%	1.122
6#	IO-Double	11.31	16.89	[2.52,3.08]	4000	[0.3,0.6]	m=0.06115 w=0.02319	5.23%	1.128
7#	IO-Double	11.31	16.89	2.8	[3600,4400]	[0.3,0.6]	m=0.06126 w=0.02538	5.42%	1.120
8#	IO-Multiple	11.32	16.88	[2.52,3.08]	[3600,4400]	[0.3,0.6]	m=0.06145 w=0.02619	5.75%	1.180

Tab. 7 shows the optimization results of the 6σ optimization scheme and the uncertain interval optimization scheme. From the double interval uncertain optimization (5#-7#) and the multi-interval uncertain optimization (8#) to analyze.

Double-interval uncertain optimization: 2# decreases EEOI value by 8.14%, 3# decreases EEOI value by 8.17%, 4# decreases EEOI value by 3.03%, 5#(compared with 2#, 3#) decreases EEOI value by 7.5%, 6# (compared with 2#, 4#) increases EEOI value by 5.23%, 7# (compared with 3#, 4#) increases EEOI value by 5.42%, indicating that the coupling effect of the two uncertain factors inhibits the energy-saving effect of EEOI. And the coupling effect of *Vw-S* increases EEOI value by 8.81%, the coupling effect of *Vw-R* increases EEOI value by 10.34%, and the coupling effect of *S-R* increases EEOI value by 10.56%. Among them, the coupling effect of *S-R* has the greatest influence on EEOI.

Multi-interval uncertain optimization: 8# is the optimization result of the optimal scheme when three uncertain factors exist together. Compared with single and double uncertain factors, when multiple uncertain factors are together, the optimal value of EEOI is the largest, and its energy-saving effect is the weakest. This shows that as uncertain factors increase, the energy-saving effect of EEOI weakens. Therefore, in actual engineering optimization, it is often necessary to consider the effect of uncertain factors on the objective function and ignore some optimization objective values to ensure the feasibility of the optimization scheme.

Compared with 6σ optimization (1#), EEOI value of single-interval uncertain optimization (2-4#) decreases by 4.43% on average, EEOI value of double-interval uncertain optimization (5-7#) increases by 1.05% on average, and EEOI value of multi-interval uncertain optimization (8#) increases by 5.75% on average. However, the quality level of the uncertain interval optimization scheme is low, only between 1.1-1.4σ, and the reliability of the scheme is low. Follow-up reliability analysis can be carried out to improve its reliability.

The interval analysis method is used to analyze the uncertainties, so as to reduce the CO2 emission to a certain extent and improve the energy efficiency operational level of ships. Where *R* has the greatest affected on EEOI, *S* and *Vw* have basically the same affected on EEOI, and the coupling effect of uncertain factors is to inhibit EEOI, which is similar to profile optimization[24].

5 Conclusions

By taking the YUKUN ship as the research object, this research develops a speed optimization design. According to the actual navigation, the speed data obtained are analyzed, and appropriate speed data are selected as the design variables. Through this, a deterministic optimization scheme is formulated, and the σ level of the output responses is analyzed. The interval analysis method is used to embed uncertain factors into the double-layer nested optimization system and to formulate an uncertain interval optimization scheme. The effects of the coupling effect of uncertain factors on EEOI are analyzed, and the following conclusions are drawn:

1. Acquisition of speed data: To obtain the available speed data, first, the Lagrange quadratic interpolation polynomial is used to conduct the time equidistantization of speed. Second, the *Findpeaks* function is used to intelligently segment the maximum and minimum values of the speed data. Then, stationary phase data are expanded based on cloud model theory. The expanded data are abundant. Finally, The *Normplot* function is used to evaluate the normality of data. For the optimization design, $\mu \pm 3\sigma$ is selected as the design variable.

2. Deterministic optimization: ASA is used to formulate deterministic optimization. When the optimal scheme is found in 1,945 steps, the EEOI value is 0.05402. Using 6σ analysis for reliability analysis, the reliability and σ level of the output response are found to be low. After 6σ optimization, each output response reaches the 6σ level and above, and reliability reaches 100%. However, the EEOI value increases, and the energy-saving effect weakens.

3. Uncertain interval optimization: The interval analysis method is used to embed uncertain factors into the double-layer nested optimization system to examine the effect of the uncertain factors (*Vw*, *S* and *R*) on EEOI. Among these, *Vw* and *S* promote and enhance the energy-saving effect of EEOI. When multiple uncertain factors exist, the coupling effect of uncertain factors is to inhibit EEOI, and the increase in uncertain factors also decreases the energy-saving effect of EEOI. However, considering the actual operation process, uncertain factors are inevitable. The introduction of uncertain factors ensures the feasibility of the operation scheme.

4. This research is based on a voyage from Dalian to Haiyang Island of the YUKUN ship to simulate the energy efficiency operation scheme of ship navigation. It also analyses the effects of uncertain factors and their coupling on EEOI. The next step is to examine the specific effect of the ship cargo load rate *R* on EEOI or how to improve the reliability of uncertainty interval optimization.

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