Research on Multi-interval Coupling Optimization of Ship Main Dimensions for minimum EEDI

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Abstract

In order to improve energy-saving effect of the YUKUN ship, minimize the value of the Energy Efficiency Design Index (EEDI), while considering the impact of uncertain factors. In this research, interval analysis method is used in uncertain optimization, and main dimensions of interval optimization research for EEDI are carried out. First, multi-island genetic algorithm (MIGA), particle swarm optimization (PSO) and adaptive simulated annealing algorithm (ASA) optimization methods are used for deterministic optimization, to analyze the influence of different optimization algorithms on the optimization results and to obtain the best deterministic optimization scheme. Second, considering uncertain factors—flow velocity V_W, ship's wet surface area S and total resistance coefficient C_t—the interval analysis method is used to determine the main dimensions of the optimization problem and to analyze the influence of single interval and multi-interval coupling on the EEDI. Analysis shows that an increased number of uncertain factors will increase EEDI while decrease the energy saving effect, as will the coupling effect between uncertain factors. Final value of EEDI obtained by multi-interval coupling optimization, however, can be more realistic and guarantees the reliability of the scheme of the ship's main dimensions, and also be feasible as is still below the required baseline.

Key words: EEDI; Deterministic optimization; Uncertainty; Interval analysis method; Coupling effect

0 Introduction

Today's environmental problems and global warming are gradually intensifying. In order to control CO_2 emissions from the shipping industry, special studies on CO_2 emissions from ships were conducted at the 56th through 59th Marine Environmental Protection Committee (MEPC), and the

Energy Efficiency Design Index (EEDI) was ultimately proposed. It is mandatory for new shipbuilding to meet the energy efficiency standards for CO_2 emissions during conceptual design and construction[1].

The relationship between the EEDI and the main dimensions of conceptual ship design will first be discussed. Wang[2] et al. took VLCC as the research object, adopted affine transformation and the Lackeby method, and obtained a fast and effective EEDI-oriented main ship dimensions optimization method under the constraint of minimum propulsion power. Su[3] et al. took a multi-purpose ship as the research object, parameterized the ship's resistance and the EEDI according to the Pruhaska hypothesis and the three-dimensional conversion algorithm, and used the NSGA-Ⅱ algorithm to obtain optimized main dimensions for the ship. Hasan[4] obtained main design dimensions in line with the EEDI baseline formula by analyzing a large amount of data. Kristensen[5] analyzed the main dimensions of oil tankers and bulk carriers over the past 30 to 40 years and made recommendations for the main dimensions of new-built tankers and bulk carriers, which can decrease EEDI value by 10~15%. The above research shows the importance of the main dimensions in calculating the EEDI. Therefore, this research defines the main dimensions as a design variable and takes the EEDI as the objective function for optimization.

However, in conceptual design, the uncertainty of certain parameters is unavoidable, as a constant value would cause errors in the results. HANNAPEL[6-7] of the University of Michigan proposed a parallel optimization method based on reliability design and robustness design and used it in the conceptual design of bulk carriers, indicating that it is very important to consider uncertain factors in the multidisciplinary design of ships. Diez[8] considered the uncertain factors of operation and environment and adopted a robust optimization method to minimize the mean and variance of transportation costs. Hou[9-10] et al. studied the optimization method of mixed uncertainty analysis based on randomness and cognition and completed an optimization design of hull lines for minimum EEDI by quantitatively describing the 6σ theory of uncertainty levels and introducing it into the USV navigation performance optimization model to obtain a reasonable and highly reliable optimization scheme. Liang[11] et al. considered the uncertainty of the AUV hull lines and used the 6σ method to optimize them lines. Li[12] et al. used ship speed and draft as uncertain factors and used a new multi-dimensional polynomial chaos method to complete the multi-disciplinary robust design optimization of OSV. The above research shows that the influence of design variables and uncertain factors must be considered in the optimization process, that effective and reliable design results can be obtained.

Applying the uncertain method to the conceptual design of ships will make the design optimization plan more reasonable, more realistic and more feasible. There are many uncertainty methods, which can be divided into three categories: stochastic programming, fuzzy programming and interval programming. Moore[13] proposed the interval algorithm in the late 1950s. The interval analysis method is considered to have application potential in the actual design analysis of engineering structures. The application of this method can, to a certain extent, avoid the deviation caused by errors in engineering practice. Li[14] et al. applied the interval analysis method in the process of uncertain robust design to ensure the robustness of ships. Qiu[15] et al. proposed an interval analysis method for eigenvalue problems with uncertain parameter structures, which showed that this method is effective in such cases. The uncertain factors in the interval analysis method are expressed by intervals, which somewhat decreases the number of samples. The calculation process is relatively simple, saves time and decreases the difficulty of the work, which has certain advantages in the engineering structure, so this research applies the interval analysis method to uncertainty optimization.

This research takes the YUKUN ship as the mother ship for the design of the ship's main dimensions. First, it uses deterministic thinking for deterministic optimization. Then, the interval analysis method is used to construct an uncertain double-layer nested optimization system and the impact of a single interval uncertain optimization on the performance of the EEDI is considered. Finally, multi-interval uncertain optimization is analyzed. as the number of uncertain factors increases, so does the impact of mutual coupling of uncertain factors on the performance of the EEDI.

1 EEDI baseline formula

EEDI's baseline formula is a standard for whether newly designed ships meet energy efficiency requirements. According to the "Interim Guidelines for the Calculation Method of Energy Efficiency Design Index for New shipbuilding", EEDI achieved by the ship design shall not be greater than EEDI required by the standard.

$$\mathrm{A}_{\mathrm{AttainedEEDI}} \leq R_{RequiredEEDI} = \left(1 - \frac{X}{100}\right) \times R_{ReferenceLineValue} \tag{1}$$

where: $\mathrm{A}_{\mathrm{AttainedEEDI}}$ is EEDI achieved by the ship design, $R_{RequiredEEDI}$ is EEDI required by the standard, X is Corresponding reduction in phases, $R_{ReferenceLineValue}$ is EEDI baseline.

The baseline formula of the energy efficiency design index for new shipbuilding was originally calculated by Denmark based on the data in the Fairplay of Lloyd's Register of Shipping, combined with the preliminary EEDI calculation formula at the time, and through certain assumptions, EEDI of these ships was calculated. Taking $Capacity$ as the independent variable, using the exponential function to perform regression analysis on EEDI calculation results of these ships by ship form, and get the corresponding values of a and c. The proposal MEPC58/4/8 was submitted before the 58th session of MEPC[16].

$$R_{ReferenceLineValue} = a \times Capacity^{-c} \tag{2}$$

where: $a,\ c$ are the ship form coefficients of statistical analysis, $Capacity$ is the load capacity of the ship.

In the 58th meeting of MEPC, Danish experts made assumptions based on the ship data in the LRFP database of Lloyd's Register of Shipping:

1) The conversion coefficient between fuel consumption and CO_2 emissions is both taken as

$C_{FME} = C_{FAE} = C_{Feff} = 3.114$;

2) The fuel consumption of the main engine is $SFC_{ME} = 190\,\mathrm{g/KW \cdot h}$, and the fuel consumption of the auxiliary engine is $SFC_{ME} = 215\,\mathrm{g/KW \cdot h}$;

3) Host power is $P_{ME} = 75\% MCR_{ME}$;

4) Auxiliary power is:

$$P_{AE} = \begin{cases} 0.025 \cdot MCR_{ME} + 250 & (MCR_{ME} \geq 10000KW) \\ 0.05 \cdot MCR_{ME} & (MCR_{ME} < 10000KW) \end{cases} \tag{3}$$

5) All correction factors f_j, f_i, f_w are equal to 1;

6) Innovative new energy technologies and additional propulsion power are not considered. $P_{AEeff} = P_{PTI} = P_{eff} = 0$;

7) Δ is the loading capacity of the ship, usually expressed in deadweight tonnage.

The simplified formula is:

$$EEDI = 3.114\frac{190P_{ME}+215P_{AE}}{\Delta \cdot V_{ref}} \tag{4}$$

Through various comparisons of EEDI, the main decisive factors for the new shipbuilding energy efficiency design index are the still water speed V_{ref}, the deadweight or gross tonnage $Capacity$, and the power P_e required to reach this speed.

2 Numerical modeling

The ship energy efficiency design index is evolved from the "new shipbuilding CO_2 design index", to measure the CO_2 efficiency of ships. EEDI is the environmental cost (CO_2 emissions) generated by the social benefits (freight volume) created by each unit of transportation in the ship design process.

The ship energy efficiency design index formula can be simplified as shown below, which can be understood from the two parts of the numerator and denominator:

$$EEDI = \frac{P_e \cdot SFC \cdot C_f}{Capacity \cdot V_{ref}} \tag{5}$$

where: The numerator part is the CO_2 emissions during the ship's voyage; the denominator part is the ship's cargo capacity. P_e is the effective power of the ship during navigation, SFC is main engine fuel consumption rate, C_f is fuel carbon conversion coefficient, $Capacity$ is load capacity of the ship, V_{ref} is still water speed of the ship.

Formula (5) shows that EEDI is related to the ship's effective power P_e, carrying capacity $capacity$ and still water speed V_{ref}.

The still water speed V_{ref} can be estimated by the main parameters of ship form, the formula is as follows:

$$V_{ref} = 1.81 \cdot \sqrt{L_{PP}}\sqrt[4]{\frac{BHP}{K \cdot \Delta}} \tag{6}$$

Taking the displacement of the ship $\Delta = \rho \cdot L_{PP} \cdot B \cdot d \cdot C_b$ into formula (6), to shows still water speed V_{ref} is related to ship forms parameters of the L_{PP}、B、d and C_b.

The ship's effective power P_e adopts the mechanical formula:

$$P_e = R_t \cdot V_{ref} \tag{7}$$

Calculation of total resistance R_t adopts the empirical formula:

$$R_t = \frac{1}{2} \cdot S \cdot \rho \cdot V^2 \cdot C_t \tag{8}$$

The ship's effective power P_e is related to the ship's wet surface area S, the ship's speed V

and total resistance coefficient C_t.

$Capacity$ is equal to the difference between displacement and empty ship weight:

$$Capacity = \Delta - LW \tag{9}$$

The empty ship weight LW is composed of three parts: the weight of the steel hull W_h, the weight of the wooden outfitting W_o, and the weight of the electromechanical equipment W_m. The method of estimating the weight of the steel hull W_h adopts the statistical formula of regression analysis, the method of estimating the weight of wooden outfitting W_o adopts the cubic modulus method, and the method of estimating the weight of electromechanical equipment W_m is the statistical method of regression formula. Available ship load capacity $Capacity$ is:

$$Capacity = \rho \cdot L_{PP} \cdot B \cdot d \cdot C_b - \left[3.90 \cdot K \cdot \mathrm{L_{PP}}^2 \cdot B \cdot (C_b + 0.7) \cdot 10^{-4} + 1200\right] - C_o \cdot \mathrm{L_{PP}} \cdot B \cdot D - C_m \cdot (P_e/0.7355)^{0.5} \tag{10}$$

Formula (10) shows that the capacity of the ship $Capacity$ is related to L_{PP}、B、d、D and C_b ship form parameters.

3 Interval analysis method

There are three categories to uncertain optimization problems: stochastic programming, fuzzy programming and interval programming. The theory of stochastic programming is relatively mature and widely used, but it is difficult to obtain accurate probability distributions from practical problems. Research on fuzzy linear programming is relatively mature, but fuzzy nonlinear programming needs further research. Interval programming is a relatively new research field that has started to study the problem of uncertain interval optimization. The interval analysis method does not require the exact probability distribution or fuzzy membership function, and the variation range of the uncertainty parameter is expressed by the interval. This means it can somewhat reduce the amount of sample information required, so it is increasingly used in optimized ship design.

Interval is a bounded closed set of real numbers, which can be expressed as[17]:

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

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

Interval can also be described as:

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

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

When there are uncertain factors in the problem and the interval analysis method is used, uncertain interval optimization problem can be expressed as:

$$\begin{cases} \min F(X,R) \\ s.t.\ g_j(X,R) \le b_j^I = \left[b_j^L, b_j^U\right],\ j = 1,2,\cdots l,\ X \in \Omega^n \\ R \in R^I = [R^L, R^U],\ R \in R_i^I = \left[R_i^L, R_i^U\right],\ i = 1,2,\cdots q \end{cases} \tag{13}$$

where: X is design variable, R is uncertain variable, F and g are objective function and constraint function respectively, which are nonlinear continuous function of design variable X and uncertain variable R. R is a fluctuation range, for any X, The values of the objective function and the constraints constitute an interval.

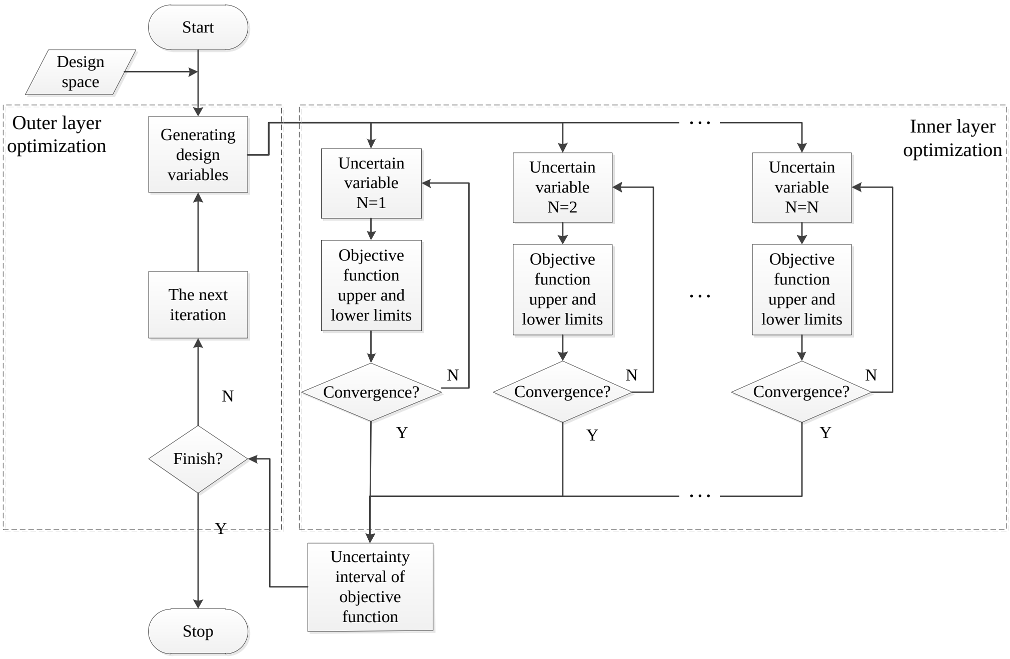


Fig. 1 Flow chart of multi-interval and double-layer nesting

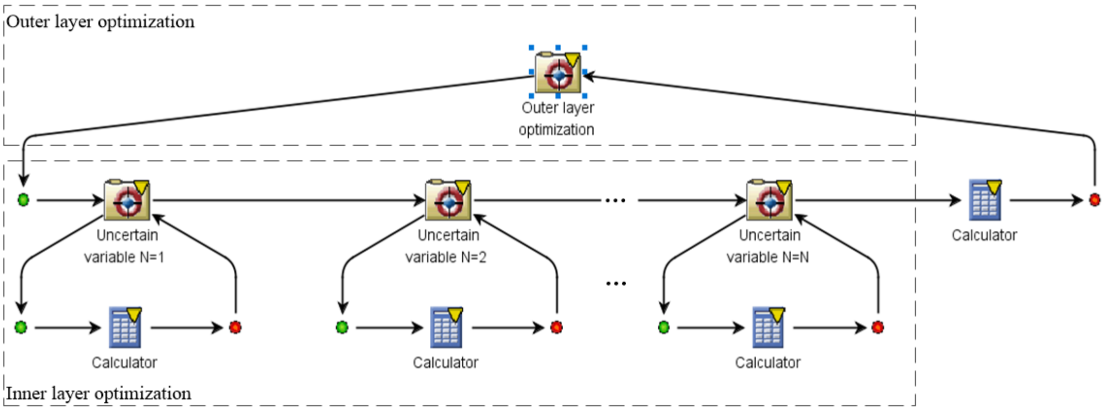


Fig. 2 Uncertain interval optimization framework

Fig. 1 presents a flow chart of multi-interval and two-layer nested optimization. The interval analysis method is used to embed uncertain factors into the optimization system, and N uncertain factors establish N working conditions. Taking an uncertain factor as an example, the optimization algorithm and design variables in the design space are first selected and then passed to inner layer optimization. Inner layer optimization occurs when the design variable takes a fixed value, the uncertain factor is expressed by the interval number and, at the same time, the appropriate optimization algorithm is selected to calculate the upper and lower limits of the uncertain interval optimization objective function. If it converges, the uncertain interval of the objective function is passed to outer layer optimization. Outer layer optimization is used mainly to search for design variables and find the optimal solution. If it converges, stop the iteration; if it does not, continue to iterate until it converges. Fig. 2 shows the uncertain interval optimization framework established in ISIGHT.

4 Deterministic optimization

In the field of ship design, optimized design involves economic indicators, hydrodynamics, structural strength, material technology, manoeuvrability, stability and buoyancy. At present, conventional methods of conceptual ship design are based on deterministic thinking to achieve optimal ship performance. The YUKUN ship is taken as the mother ship, and its main parameters are shown in Tab. 1.

Tab. 1 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

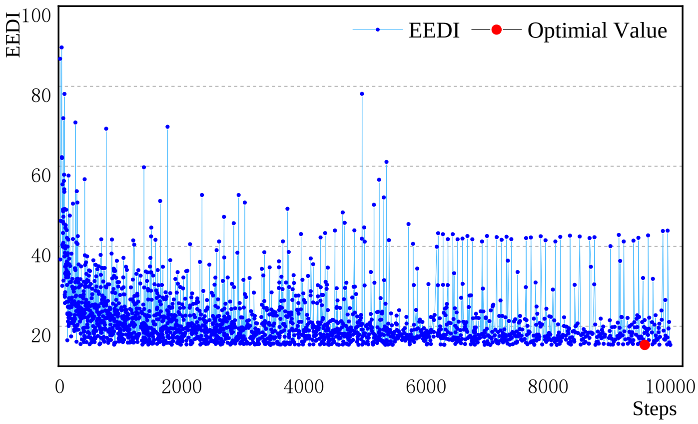
With L_{PP}、B、D、d、C_b as design variables, the constraints are the main dimension ratio constraints, buoyancy, resistance constraints and initial stability inequality constraints, and the goal is to find the smallest EEDI. As shown in Tab. 2.

Tab. 2 Value ranges and initial values of design variables and constraints

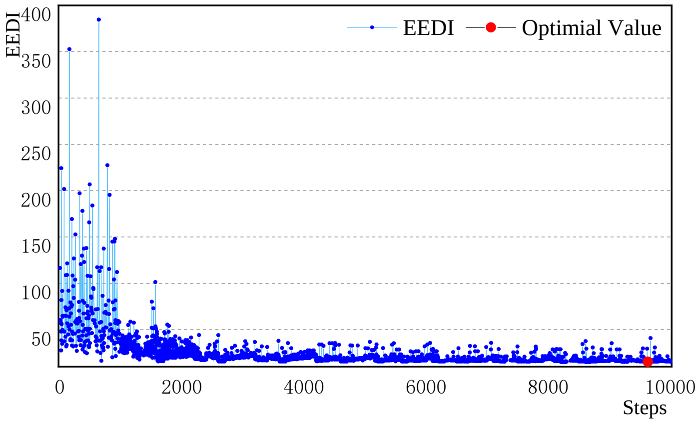
		Upper limit	Lower limit	Initial value
Design variable	Length between perpendiculars $L_{PP}(m)$	120	90	105
	Moulded beam $B(m)$	22	14	18
	Moulded depth $D(m)$	10	6	8.35
	Design draft $d(m)$	7	4	5.4
	Block coefficient C_b	0.7	0.5	0.5596
Restrictions	L_{PP}/B	7	5.5	5.83
	L_{PP}/D	14	10	12.57
	B/d	4	2	3.33
	B/D	2	1.2	2.15

4.1 Deterministic optimization results

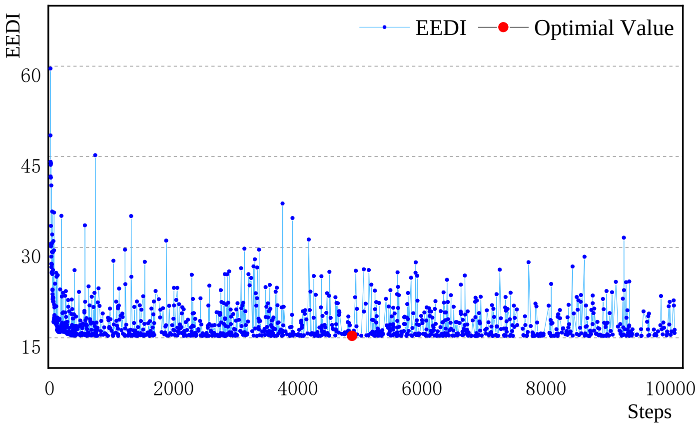
Different optimization algorithms (particle swarm optimization [PSO], multi-island genetic algorithm [MIGA] and adaptive simulated annealing algorithm [ASA]) are used to deterministically optimize EEDI, and three optimization schemes are calculated.



(a) PSO algorithm



(b) MIGA algorithm



(c) ASA algorithm

Fig. 3 EEDI optimization curve of different optimization algorithms

Fig. 3-(a) presents the EEDI optimization curve obtained by 10,000 iterations of PSO. PSO adopts the principle of evolutionary calculation and was originally designed to study the predation behaviour of birds and search for optimal particles in the solution space. PSO has no genetic algorithm crossover or mutation operations, it is simple and easy to implement and it does not have too many parameters to adjust.

Fig. 3-(b) presents the EEDI optimization curve obtained by 10,000 iterations of the MIGA. Genetic algorithms mainly rely on the law of "survival of the fittest" in biological processes. Encode

the individual in the solution space of the optimization problem. Then, genetic operations are performed on the encoded individual population, and the new population is iteratively searched for the optimal solution or a combination of better solutions. MIGA is an improved version of a genetic algorithm, with better global solving ability and computational efficiency than traditional genetic algorithms.

Fig. 3-(c) presents the EEDI optimization curve obtained by 10,000 iterations of the ASA. ASA is similar to a genetic algorithm in that new design points are generated from the mutation of old design points, but ASA detects only one design point in the search space, and the objective function is evaluated once every step forward from the initial point. As long as the function value declines, the new design point is accepted, and the process is repeated until the best point is found. ASA has better overall solving ability and computational efficiency.

Fig. 3 shows that the EEDI optimization curves of the three optimization algorithms used are all random in the initial stage, with large fluctuations up and down. As the number of iterations gradually converges, PSO tends to converge at step 250, MIGA tends to converge at step 1000, and ASA tends to converge at step 100. The optimization results of the EEDI of the three optimization algorithms differed slightly, by around 15.3. ASA finds the best in step 4874, compared with the other two optimization algorithms, calculation time is greatly saved, it is more appropriate for formulating deterministic optimization.

Tab. 3 Deterministic optimization results of different optimization algorithms

Case	Optimization method and Algorithm	Design variable selection $\{L_{PP}、B、D、d、C_b\}$	Best steps	EEDI	Relative mother ship /%
S1#	Baseline value	-	-	21.58	-
S2#	Mother ship	{105、18、8.35、5.4、0.5596}	-	20.45	-
S3#	DO-MIGA	{119.94、21.80、8.56、6.99、0.699}	9632	15.332	-25.02%
S4#	DO-ASA	{119.99、21.81、8.57、6.99、0.699}	4874	15.307	-25.14%
S5#	DO-PSO	{120、21.81、8.59、7、0.7}	9581	15.311	-25.12%

Tab. 3 shows the optimal EEDI corresponding to the different optimization algorithms. MIGA reaches the optimum at step 9632, ASA reaches the optimum at step 4874 and PSO reaches the optimum at step 9581. The optimization results of the three optimization algorithms are all below the baseline and are better than those of the initial scheme, indicating that there is room for optimization in the initial scheme. The optimization result of PSO is 25.12% higher than the performance of mother ship EEDI, the optimization result of MIGA is 25.02% higher and the optimization result of ASA is 25.14% higher. The ASA algorithm shows the largest improvement in EEDI and the least time required for calculation, meaning it can quickly find the best solution and ensure that the quality of the optimization solution meets the standard after convergence. Therefore, the deterministic optimization of ASA is optimal and is used for the following uncertainty interval optimization and comparison.

4.2 Sensitivity analysis

Taking optimized result of ASA algorithm as the initial value, Monte Carlo is used for sensitivity analysis in ISIGHT. The selected probability density function is the normal distribution function, and descriptive sampling method is used to sample 10,000 times to obtain the influence of design variables on EEDI.

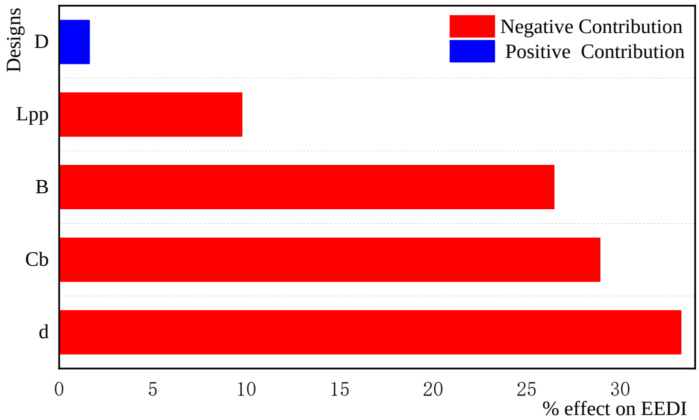


Fig. 4 Contribution rate of design variables

Fig.4 shows ship's design draft d, block coefficient C_b, and moulded beam B have a greater impact on EEDI, which can cause large fluctuations. D is positively correlated with EEDI, while d, C_b, B and L_{PP} are negatively correlated with EEDI, and the contributions of d, C_b, B are high, so the values of d, C_b, B in the optimal solution are relatively high.

5 Uncertain interval optimization

This research uses the YUKUN ship as the mother ship and applies the interval analysis method to the ship's conceptual design. The design variables are length between perpendiculars, moulded beam, moulded depth, design draft and block coefficient. The flow velocity V_W, ship's total resistance coefficient C_t and ship's wet surface area S are taken as uncertain variables, the uncertain factors in the actual project are considered and the value range is 10% above and below the initial value. The median and radius of the EEDI are used as optimization targets. The paper also discusses the influence of a single uncertain factor and multiple uncertain factors as well as the coupling effect of multiple uncertain factors on the objective function.

Tab. 4 Values of uncertain factors

Uncertainties	Initial value	Lower limit	Upper limit
Flow velocity V_W	2.8	2.52	3.08
Total resistance coefficient C_t	0.003	0.0027	0.0033
Ship's wet surface area S	4000	3600	4400

5.1 Single Uncertain factor

When examining the influence of a single uncertain factor on the objective function, the influence of flow velocity V_W, the ship's total resistance coefficient C_t and the ship's wet surface area S on the median and radius of the EEDI are considered separately. The two-layer nested optimization system is established according to the research of Li et al.[14] on the uncertain and robust optimization design of ships. The outer layer uses the second-generation non-inferior sorting genetic algorithm (NSGA-Ⅱ), which has strong exploration performance, wide search range and high degree of group collaboration. the population size is set to 40 and the genetic algebra to 50.The inner layer adopts the multi-island genetic algorithm MIGA, which has better global search capabilities and computational efficiency, and the subgroup size, number of islands and number of genetic algebras are all set to 5. A two-layer nested optimization system is used to solve the median and radius of the EEDI. The optimization results are shown in Tab. 5.

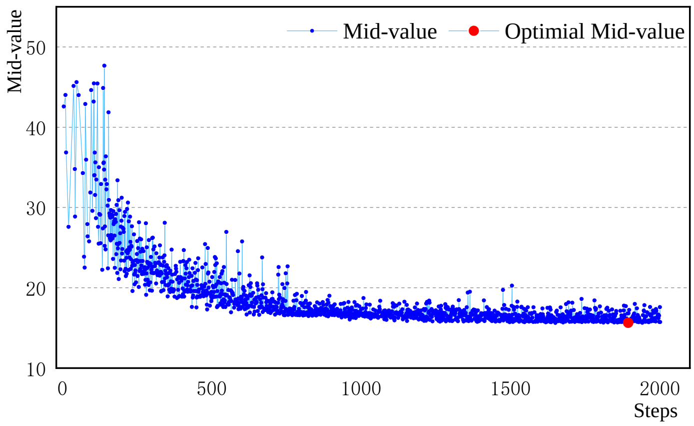
Tab. 5 Optimization results of the uncertainty interval of a single uncertainty factor

Case	Optimization method	L_{PP}、B、D、d、C_b	V_w	C_t	S	Median and radius of EEDI	Relative to ASA /%
M1#	DO	{119.94、21.80、8.56、6.99、0.699}	2.8	0.003	4000	-	0.16%
M2#	DO	{119.99、21.81、8.57、6.99、0.699}	2.8	0.003	4000	-	0
M3#	DO	{120 、 21.81 、8.59、7、0.7}	2.8	0.003	4000	-	+0.02%
M4#	IO-Single	{119.99、21.80、8.70、6.99、0.699}	[2.52,3.08]	0.003	4000	m =15.637 w =0.325	+2.15%
M5#	IO-Single	{119.89、21.79、8.68、6.99、0.698}	2.8	[0.0027,0.0033]	4000	m =15.380 w =0.912	+0.47%
M6#	IO-Single	{119.73、21.62、9.42、6.99、0.699}	2.8	0.003	[3600,4400]	m =15.504 w =0.917	+1.28%

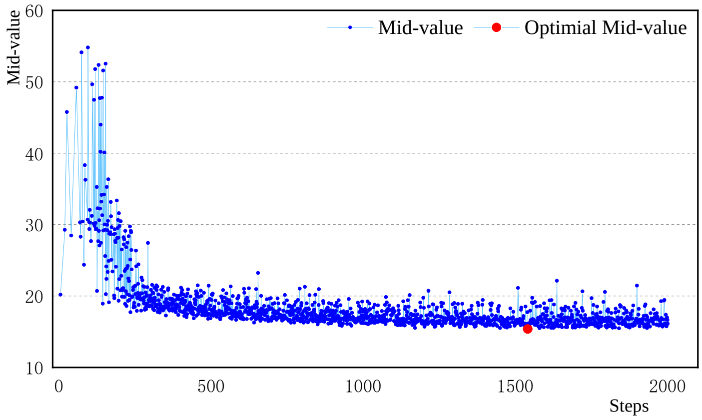
Comparing the following things to the ASA, flow velocity V_W increases the value of the objective function by 2.15%, total resistance coefficient C_t increases the value of objective function by 0.47% and the ship's wet surface area S increases the value of objective function by 1.28%. The selected uncertain factors have a negative influence on objective function, all of which increase value and weaken performance.

M4#~M6#: the median EEDI of the optimization results is around 15.5. Under the influence of V_W, the radius of EEDI is only 0.325, and the fluctuation range is small, indicating that V_W has strong robustness to EEDI. C_t and S have basically the same radius of EEDI, both around 0.91. Explain that C_t and S have the same robustness to EEDI.

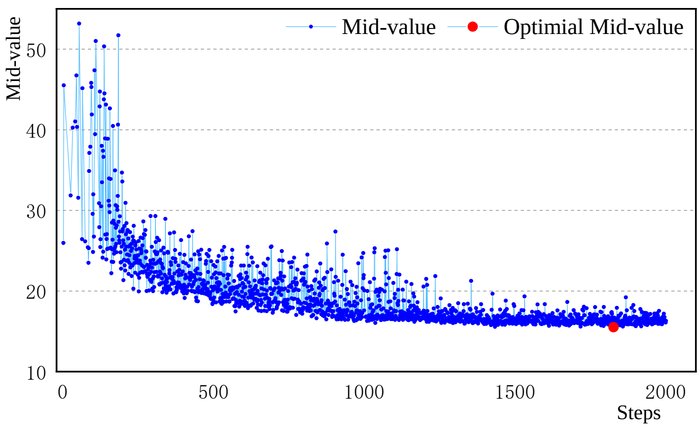
M5#: C_t has little effect on the EEDI and increases only by 0.47% relative to ASA deterministic optimization, but the resulting EEDI radius is 0.912. This shows that C_t has weak robustness to EEDI but still produces a better value than that of the mother ship. Therefore, the interval analysis method is introduced to uncertain optimization to decrease the influence of uncertain factors on the objective function and ensure the ship's main dimensions scheme has practical operability.



(a) Flow velocity V_w



(b) Total resistance coefficient C_t



(c) Ship wet surface area S

Fig. 5 The median optimization curve of EEDI under single uncertainty

Fig. 5 shows that, in the initial stage, three uncertain factors are selected randomly and the median fluctuation range of the corresponding EEDI is relatively large. This was to achieve global optimization and avoid local optimization, continuously determine the optimal lower limit and narrow the fluctuation range of the objective function until convergence. Fig. 5 illustrates that under the influence of flow velocity V_W, EEDI iterated 700 times to reach convergence; under the influence of total resistance coefficient C_t, EEDI iterated 300 times to reach convergence; and under the influence of the ship's wet surface area S, EEDI iterated 1000 times to reach convergence.

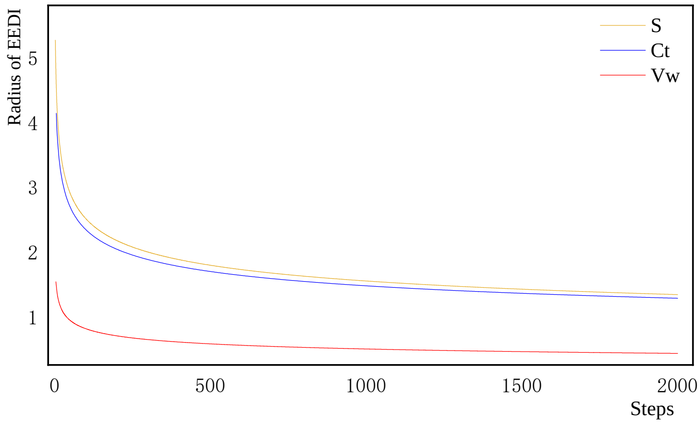


Fig. 6 Fitting diagram of radius convergence of EEDI under single uncertainty

Fig. 6 shows that the radius fluctuation ranges of S and C_t are basically the same, but the radius fluctuation range of V_w is smaller. It also shows that S and C_t have the same influence on EEDI, and V_W has a weaker influence on EEDI. The robustness of EEDI under the influence of V_W is strong, which indicates that the use of interval analysis method in uncertainty optimization is beneficial to the robustness of ships.

5.2 Multiple uncertain factors

To further explore whether the objective function is related to the number of uncertain factors, the influence of the coexistence of two uncertain factors and of multiple uncertain factors on the objective function is studied, and the mutual coupling relationship when multiple uncertain factors coexist is analyzed. The existence of two or more uncertain factors of V_w, S and C_t enables the study of changes in the median value and radius of the objective function.

Tab. 6 Optimization results of uncertainty interval under multiple uncertain factors

Case	Optimization method	Genetic algorithm	V_w	C_t	S	Median and radius of EEDI	Relative to ASA /%
M1#	DO	MIGA	2.8	0.003	4000	15.332	-
M2#	DO	ASA	2.8	0.003	4000	15.307	-
M3#	DO	PSO	2.8	0.003	4000	15.311	-
M4#	IO-Single	Inner：MIGA Outer ： NSGA-II	[2.52,3.08]	0.003	4000	m =15.637 w =0.325	+2.15%

M5#	IO-Single	Inner：MIGA Outer ： NSGA-Ⅱ	2.8	[0.0027,0.0033]	4000	m =15.380 w =0.912	+0.47%
M6#	IO-Single	Inner：MIGA Outer ： NSGA-Ⅱ	2.8	0.003	[3600,4000]	m =15.504 w =0.917	+1.28%
M7#	IO-Double	Inner：MIGA Outer ： NSGA-Ⅱ	[2.52,3.08]	[0.0027,0.0033]	4000	m =15.972 w =1.178	+4.34%
M8#	IO-Double	Inner：MIGA Outer ： NSGA-Ⅱ	[2.52,3.08]	0.003	[3600,4400]	m =15.819 w =1.289	+3.34%
M9#	IO-Double	Inner：MIGA Outer ： NSGA-Ⅱ	2.8	[0.0027,0.0033]	[3600,4400]	m =15.699 w =1.548	+2.56%
M10#	IO-Multiple	Inner：MIGA Outer ： NSGA-Ⅱ	[2.52,3.08]	[0.0027,0.0033]	[3600,4400]	m =16.353 w =1.448	+6.83%

Tab. 6 shows the comparison of the optimization results of deterministic optimization, single-interval uncertain optimization and multi-interval uncertain optimization. The inner layer of the two-layer nested optimization system adopts the MIGA algorithm, and the outer layer adopts the NSGA-Ⅱ algorithm and the influence of uncertain factors on the median and radius of EEDI are compared.

Compared with the deterministic optimization of ASA, M7# decreases EEDI by 4.34%, M8# decreases EEDI by 3.34% and M9# decreases EEDI by 2.56%. Then, the EEDI that was optimized by multi-interval uncertainty is decreased by 6.83%. Tab. 6 shows that compared to deterministic optimization (M2#), the single-interval uncertain optimization (M4-6#) increased EEDI by 1.30% on average (2.15%, 0.47% and 1.28%, respectively); dual-interval uncertain optimization (M7-9#) increased EEDI by 2.11% on average (4.34%, 3.34% and 2.56%, respectively). Multi-interval uncertain optimization (M10#) increased EEDI by 6.83%.

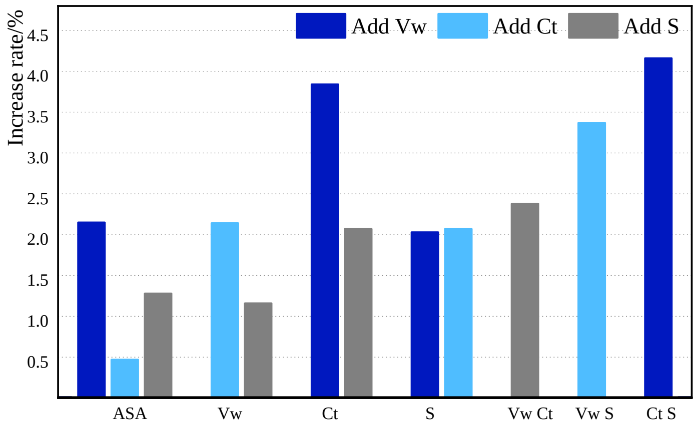


Fig. 7 Increase rate of the objective function by adding uncertain factors

Fig. 7 shows that the rate of EEDI increases when uncertain factors are added. ASA deterministic optimization (M2#), single interval uncertainty optimization (M4-6#) and dual-interval uncertainty optimization (M7-9#) respectively increase the uncertain factors (V_W C_t S) to get the relative EEDI increase rate. This shows that as uncertain factors increase, so does the value of EEDI and the rate of EEDI, which decreases the energy-saving effect.

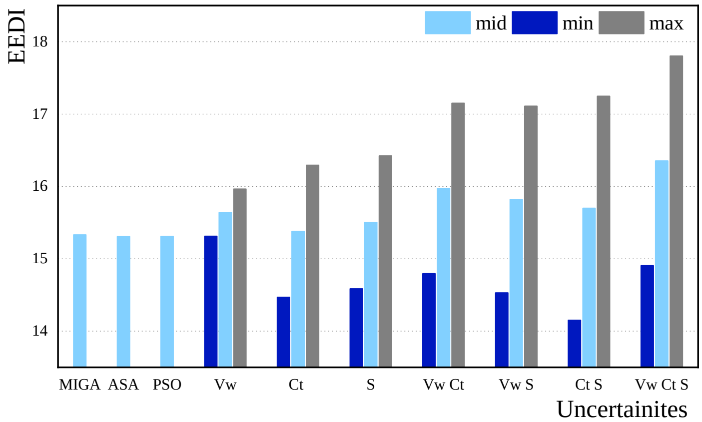


Fig.8 Comparison of the interval and median of EEDI

It can be seen from Fig. 8 that regardless of single or multiple uncertain factors, the interval of EEDI is in the range of 14-18, and the median value is around 16. Compared with the deterministic optimization results of EEDI, the value of uncertain optimization results increased, and the performance is decreased. Under the combined influence of the two uncertain factors, the median value of the objective function is larger than that of the single uncertain factor, and the fluctuation range of the radius is also increased. The objective function has weak robustness, but its optimal value is still within the baseline range, which is better than mother ship. When there are multiple uncertain factors, the optimization results of the relative single and two uncertain factors are weakened, but they are more in line with the actual ship conceptual design, and the feasibility of the scheme is higher.

6 Conclusions

In this research, YUKUN ship is used as the mother ship for optimized design of the ship's form, and deterministic optimization is carried out without considering the uncertain factors. However, uncertain factors that may lead to errors in the optimization scheme are present. Therefore, the interval analysis method is used for uncertainty optimization and is compared with the deterministic optimization results. The influence of single interval, double interval and multi-interval coupling on the objective function are analyzed, and the following conclusions are drawn:

1. Deterministic optimization: The impact of three different global optimization algorithms on the objective function of the EEDI are explored. The results obtained using the ASA algorithm are the best. In the initial stage of optimization, the fluctuation range of the EEDI using the ASA algorithm is small, convergence is achieved within just a few iterations and in the least time, and the EEDI value is only 15.307. The main characteristic of ASA is that, as long as the value of the function decreases, the new design point will be accepted, and it will continue to repeat until the best point is found. It has greater global solution ability and computational efficiency and can jump out of the local optimal solution situation to achieve the global optimal solution.

2. Interval analysis method: The traditional deterministic optimization design does not consider the influence of uncertainty on the design and cannot obtain reliable performance. However, the interval analysis method is an interval expression of uncertain factors, which is more effective than other analysis methods. In ISGHT, a two-layer nested optimization system is used to achieve interval optimization. The inner layer is the MIGA algorithm, an improved version of PDGAs, which has more global solution ability and calculation efficiency; the outer layer is the NSGA-Ⅱ algorithm, an improvement of NSGA, which decreases the complexity of calculation, improves the accuracy of optimization results and guarantees the diversity of the population.

3. Optimization of uncertainty interval: Single interval uncertainty optimization considers the effects of flow velocity V_W, the ship's total resistance coefficient C_t and the ship's wet surface area S on the EEDI; the degree of impact on the EEDI is $V_W > S > C_t$. When multiple uncertain factors exist, the optimization result of single or two uncertain factors is weaker, the value of EEDI increases and the rate of EEDI also increases, which decreased the energy-saving effect. However, the optimal value is still within the baseline range, which is in line with the actual ship's conceptual design, and the product's feasibility is high, ensuring the accuracy of the scheme.

4. The only uncertain factors used in the study are the flow velocity, the ship's total resistance coefficient and the ship's wet surface area. The next step is to analyze other external factors and increase the number of uncertain factors to determine the coupling effect. This could also change the value range of uncertain factors to enable an analysis of the impact on the EEDI.

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