Economic Parametric Optimization and Uncertainty Analysis in Ship Design using Monte Carlo Simulations

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Abstract

Economic efficiency must be considered in ship concept design. There are many uncertain internal and external factors in the ship design process. This paper concentrates on the optimization of a ship's economic performance while considering the influence of uncontrollable factors on the output response. Firstly, the economic-objective function and the mathematical optimization model of a bulk carrier are established, and design space and constraints are proposed. Secondly, two algorithms are adopted to perform deterministic multi-objectives optimization. Thirdly, sensitivity analysis of the design parameters is conducted as well as the output response uncertainty analysis based on Monte Carlo simulations. The results reveal that, when random variables obey a specific distribution, the corresponding distribution of uncertainty effects will also exist in the output response. Therefore, the necessity of uncertainty analysis in parametric ship concept design is verified.

Keywords: Ship design, economic, Optimization design, Uncertainty analysis, Monte Carlo simulation

1 Introduction

The economy of a ship, which is one of its most important properties, is usually set as a design objective in the concept optimization design. Nowadays, research of ship concept design and hull form optimization has accumulated many achievements involving various design objectives, design variables, and optimization systems [1-3], which embody the development ideas of 'from simple to complex' and 'from coarse to fine'.

There are various internal and external parameters that cannot be precisely described or obtained in the process of ship optimization design. These parameters usually participate in calculations as constants. Inevitably, these parameters fluctuate all the time according to probability distributions. This fluctuation makes the output response uncertain. Since this uncertainty would be magnified by continuous iterative optimization, the influence of these parameters has a practical significance on ship optimization design. In recent years, Diez introduced uncertainty optimization design to ship hull design systems, and a series of studies were conducted [4-6]. Diez [7] considered the uncertainty of the economic parameters of bulk carriers, and a robust optimization study was carried out. However, the uncertain parameters were only expressed in interval form; probability distributions and responses to the output have not yet been studied.

In this paper, the bulk carrier conceptual design tool by Sen and Yang [8] is referenced and redefined. An economic objective function and its mathematical model of the ship are established, and design space and constraint conditions are defined. Two optimization algorithms are adopted to conduct the economic multi-objectives optimization calculation.

Pointing to those internal parameters with random characteristics, sensitivity analysis and uncertainty analysis based on Monte Carlo simulations are carried out. As a result, the response relationship between system output and random variables is obtained, which can be used to guide future ship optimization design.

2 Establishment of optimization model

2.1 Optimization objective and derivation

The optimization function in this study can be divided into two parts: (a) a mathematical model of hull cost based on the ship's principal dimensions and form coefficient and (b) the economic model of overall cargo shipping considering the other factors in operation.

Hull cost can be calculated based on steel weight, outfitting weight, and main power:

$$C_s = 1.3(2000W_h^{0.85} + 3500W_f + 2400P^{0.8}) \tag{1}$$

In this equation, C_s is the hull cost (pounds); W_h and W_f are the steel weight and outfitting weight (t), respectively; and P is the main power of the ship (kW), which is calculated as follows:

$$\begin{cases} P = (\Delta^{(2/3)}V_k^3)/(a + b\cdot Fn) \\ a = 4977.06C_b^2 - 8105.61C_b + 4456.51 \\ b = -10847.2C_b^2 + 12817C_b - 6960.32 \end{cases} \tag{2}$$

Here, Δ is displacement (t), V_k is speed (kn), Fn is the Froude number, and C_b is the block coefficient.

The weight of each part is calculated as follows:

$$\begin{cases} W_h = 0.034\cdot L^{1.7}B^{0.7}D^{0.4}C_b^{\ 0.5} \\ W_f = L^{0.8}B^{0.6}D^{0.3}C_b^{\ 0.1} \\ W_m = 0.17P^{0.9} \end{cases} \tag{3}$$

In these equations, *L, B,* and *D* are the length between perpendiculars, breadth, and depth (m), respectively, and W_m is the mechanical and electrical equipment weight (t).

The main evaluation indexes are annual shipping cost, annual freight volume, and unit shipping cost:

$$C_{apt} = C_a / D_a \tag{4}$$

In this equation, C_{apt} is the unit transportation cost (pounds/t), D_a is the annual freight volume (t), and C_a is the annual shipping cost (pounds), which consists of three parts: shipping cost (C_c), operation cost (C_r), and voyage cost (C_v). These are calculated as follows:

$$\begin{cases} C_c = 0.2C_s, \quad C_r = 40000DW^{0.3} \\ C_v = \left(C_f + C_{po}\right)RTPA, \quad C_{po} = 6.3DW^{0.8}, \quad D_a = DW\cdot RTPA \\ C_f = 1.05\ C_d\cdot d_s\cdot P_f, \quad C_d = 0.19\times P\times 24/1000 + 0.2 \\ d_s = RTM/(24V_k), \quad RTPA = 350/\left(d_S + d_P\right), \quad d_P = 2\left(D_c/R_h + 0.5\right) \end{cases} \tag{5}$$

Here, C_f and C_{po} are fuel cost and port cost (pounds), respectively; *RTPA* is the number of round-trips a ship travels in one year; C_d is the daily consumption of oil (t); d_s is the number of shipping days; P_f is the fuel price (pounds/t), where the default is 100; *RTM* is the ship's single-trip mileage (n miles), where the default is 5,000; d_p is the ship's days in anchorage; R_h is the cargo handling efficiency (t/day), where the default is 8,000; D_c is the cargo dead weight (t); and *DW* is the dead weight of the ship (t). The latter is obtained as follows:

$$DW = \Delta - LW \tag{6}$$

Accordingly, the design variables of the optimization model in this study can be identified as: length (*L*), breadth (*B*), depth (*D*), draft (*T*), speed (V_k), and the block coefficient (C_b).

2.2 Constraints

While evaluating and optimizing the economy of a ship, the technical performance of the design should also be taken into account. Thus, it is necessary to propose constraints in the optimization model, including dimension ratio, manoeuvrability, stability, and so on. These constraints are defined as follows:

$$\begin{cases} T_1 = 5.5 - L/B \geq 0, \quad T_2 = 18 - L/D \geq 0 \\ T_3 = 20 - L/T \geq 0, \quad T_4 = 0.45 \cdot DW^{0.31} - 0.6 \cdot T \geq 0 \\ T_5 = 0.85D - T \geq 0, \quad T_{61} = DW - 25000 \geq 0, \quad T_{62} = 500000 - DW \geq 0 \\ T_7 = 0.32 - Fn \geq 0, \quad T_8 = 0.15B - GM \geq 0 \end{cases} \tag{7}$$

In these equations, T_1, T_2, T_3, and T_5 are the dimension ratio constraints to ensure feasibility, manoeuvrability, and stability; T_4, T_{61}, and T_{62} are the constraints for ship displacement; T_7 is the constraint for ship speed; and T_8 is the constraint for ship stability and seakeeping.

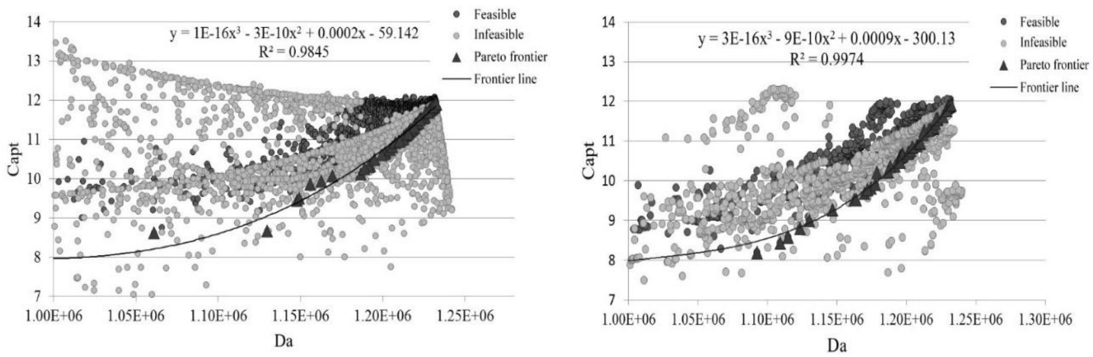
3 Deterministic parametric optimization design

In order to obtain satisfactory designs with low unit-transportation cost and high freight capacity, optimization objectives are set for the minimum unit-transportation cost (C_{apt}) and the maximum annual freight volume (D_a). Two heuristic algorithms are adopted here to achieve multiobjective optimization: adaptive simulated annealing (ASA) [9] and the multi-island genetic algorithm (MIGA) [10]. These algorithms have superior performance for nonlinear optimization problems. The parameters for the optimization model are shown in Table 1.

Table 1. Description of deterministic optimization model

Objective:
▸ Minimum C_{apt} and maximum D_a
Design variables:
▸ L: [100, 400], initial value 217 (m) ▸ B: [10, 45], initial value 32.3 (m)
▸ T: [10, 15], initial value 12.5 (m) ▸ D: [10, 25], initial value 19.7 (m)
▸ V_k: [14, 18], initial value 14.5 (m) ▸ C_b: [0.63, 0.83], initial value 0.82 (m)
Constraints:
▸ T_1–$T_8 \geqslant 0$
Constants:
▸ P_f: 100 (*pound*/*t*) ▸ *RTM*: 5000 (*n mile*) ▸ R_h: 8000 (*t*/*day*)
Optimization techniques:
▸ ASA ▸ MIGA

The main internal parameters of ASA and MIGA are set as follows: the maximum number of generated designs is 500, the relative rate of parameter annealing is 1.0, the convergence epsilon is 1e-8, the subpopulation size is 20, the number of islands is 10, and the number of generations is 10. The optimization results are shown in Figure 1.



(a) ASA (b) MIGA

Figure 1. Multiobjective optimization results graphs

Generally, the feasible solution is centralized, and the frontiers are very concentrated with a clear Pareto frontier. The point distribution of the MIGA in the optimization process is relatively more concentrated and uniform in its concentrated area. By comparison, ASA is more uneven in the optimization process: in addition to the concentration of several lines, the focus is almost exclusively on the range of 10~12 on the C_{pat} axis and 1,200,000~1,250,000 on the D_a axis. With this kind of optimal result, designer can select some excellent plans based on the frontier curve and carry out detailed design for the next step.

4 Uncertainty analysis

4.1 Sensitivity analysis

In order to analyse the influence of variable changes on the outputs, it's necessary to perform a sensitivity analysis of the design variables (L, B, D, T, V_k, and C_b) and the important constants (P_f, RTM, and R_h) toward the optimization objective.

One experiment's design technique is adopted here: the Latin hypercube design, in which the engineer has total freedom in selecting the number of designs to run. A total of 1,200 points are generated for the Latin hypercube. The main effect and Pareto contributions of C_{apt} and D_a are shown in Figures 2~5, which reflect the degree each input has an effect on each output.

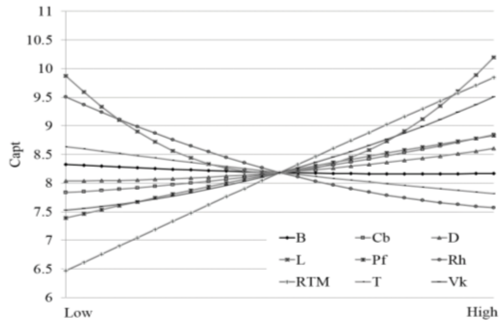


Figure 2. C_{apt} main effect graph

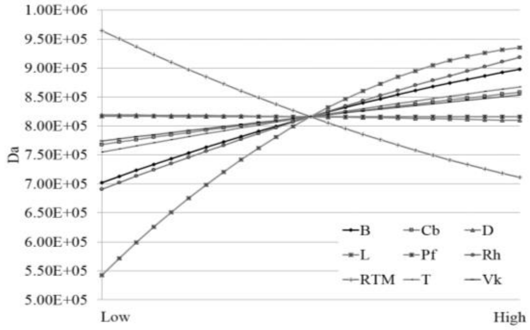


Figure 3. D_a main effect graph

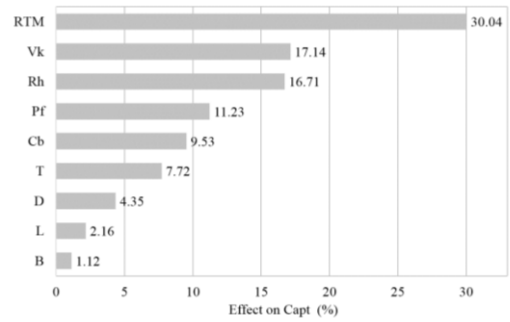


Figure 4. C_{apt} Pareto graph

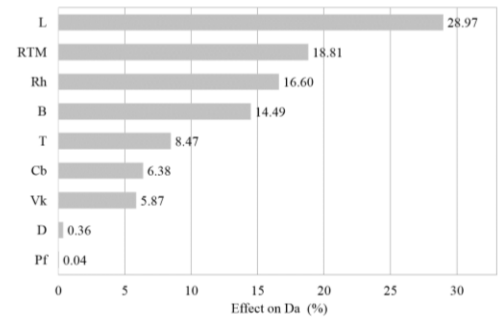


Figure 5. D_a Pareto graph

According to Figures 2 and 4, the parameters that influence C_{apt} the most are *RTM*, V_k, R_h, and P_f, and all of their contributions exceed 10%. According to Figures 3 and 5, the parameters that influence D_a the most are *L*, *RTM*, R_h , and *B*, and their contributions also exceed 10%. Therefore, uncertainty in the important constants, such as P_f, *RTM*, and R_h, would lead to uncertainty in the output and affect the whole optimization design.

4.2 Uncertainty analysis

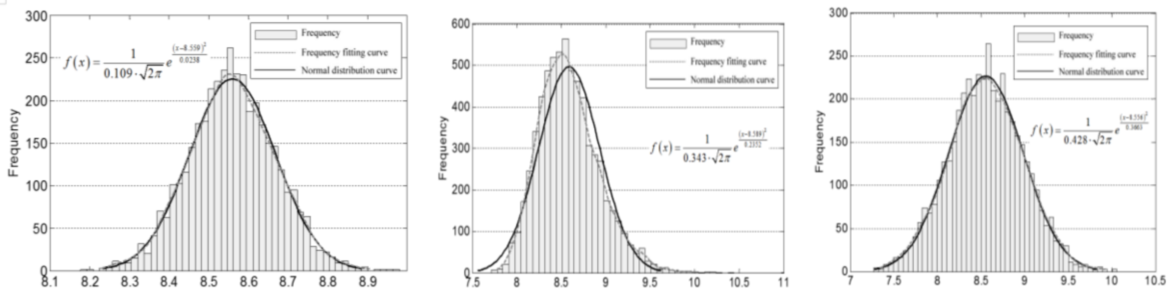
To analyse the uncertainty influence, a Monte Carlo simulation (MCS) was adopted [11]. In an MCS, the probability distribution of random variables is known. Through random sampling, the probability distribution of a system's response can be estimated, and the contribution of each random variable to the response results can be obtained.

There are two sampling techniques in an MCS: simple random sampling and descriptive sampling. Compared to the former, descriptive sampling reduces the variance of the statistical estimates derived from the population data. Descriptive sampling also ensures the quality of statistical analysis with less sampling and simulation time, so it becomes a more representative method and so is used in this study. The uncertainty analysis model is shown in Table 2.

Table 2. Uncertainty analysis model

Objective:
▸ Uncertainty influence on the optimization object
Design variables:
▸ *L*: 217 (m); ▸ *B*: 32.26 (m); ▸ *D*: 19.7 (m);
▸ *T*: 12.5 (m); ▸ C_b: 0.82; ▸ V_k: 14.5 (kn);
Uncertainty factors:
▸ P_f, Normal, μ=100 (Pound/t), σ=1%*μ
▸ *RTM*, Normal, μ=5000 (n mile), σ=1%*μ
▸ R_h, Normal, μ=8000 (t/day), σ=1%*μ
Constraints:
▸ T_1–$T_8 \geqslant 0$
Analysis Method
▸ Monte Carlo simulation: descriptive sampling

The maximum number of simulations is set at 10,000, and then a normal distribution simulation of three uncertain parameters (P_f, *RTM*, and R_h) is conducted. Their effects on the result optimization object (C_{apt}, as a more important factor to be considered,) are calculated independently. A histogram is then drawn of the frequency distribution and the frequency fitting curve according to system response parameters, a normal distribution hypothesis test is conducted, and the normal distribution curve is drawn. The influence of different parameters on the response uncertainty can then be analysed comparatively. The results of the uncertainty analysis by MCS are shown in Figure 6.



(a) P_f (b) R_h (c) RTM

Figure 6. Distribution of C_{apt} when a single parameter obeys normal distribution

A normal hypothesis test is then done. The related results and parameters are shown in Table 3.

The statistical results of the system response, C_{apt}, are shown in Table 4.

Table 3. Results of the normal hypothesis test

Input parameters	R_h obeys normal distribution separately	*RTM* obeys normal distribution separately	P_f obeys normal distribution separately
Test statistics	920.9634	1.1631	1.9229
Critical value	5.7458	6.1611	5.7143
H	1	0	0
C_{apt} obeys normal distribution?	No	Yes	Yes
P	0	0.5570	0.3790

Table 4. Statistical results of system response, C_{apt}

Statistical indicators	R_h obeys normal distribution separately	*RTM* obeys normal distribution separately	P_f obeys normal distribution separately
Expectation (E)	8.589	8.556	8.559
Standard deviation (S.D)	0.343	0.428	0.109
S.D/E	0.0399	0.0500	0.0127
Skewness	2.87E-02	2.51E-03	4.48E-05
Kurtosis	5.79E-02	9.87E-02	4.32E-04

The distribution of the system response parameters can be compared directly through the ratio of standard deviation to expectation. The ratio for R_h, *RTM*, and P_f is 0.040, 0.050, and 0.013, respectively, showing that the fluctuation of the system response parameter, C_{apt}, is more obvious with the random variable *RTM*.

As is shown, when random variables P_f and *RTM* obey normal distribution, the distribution of C_{apt} also strictly obeys normal distribution. When R_h alone obeys normal distribution, C_{apt} can also be approximated as a normal distribution. However, by comparing the standard-deviation-to-expectation ratio of the three groups of data, it can be seen that the fluctuation of the system response caused by *RTM* is more obvious.

Therefore, when the uncertainty of parameters is considered in ship design, different uncertainty parameters have different effects. The more-obviously-effect factors should be set in a more clearly pattern (probability distribution or interval, with accurate description), while the remainder can be set in an approximate range.

5 Conclusion

This research focuses on economic ship optimization design and its uncertainty analysis due to the fluctuation of internal parameters. Through the above simulation, calculation, and analysis, the response relationship between system output and random variable input is obtained, which can be used to guide the optimal design of actual ship optimization. The following conclusions are drawn:

(1) The uncertainty analysis based on MCS with descriptive sampling can clearly depict the impact of uncertain parameters on output response, thus the research conducted could hopefully promote the development of uncertainty optimization ship design.

(2) Different uncertainty parameters have different effects on the output response, thus they should be considered separately in ship design.

(3) Further studies can be conducted to investigate the properties of uncertain parameters and the applicability of uncertainty optimization algorithms with uncertainty.

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