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Optimization of Submarine Resistance and Manoeuvrability Based on SBD Technique

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ABSTRACT

A submarine usually consists of the main hull and appendages such as fairwater and rudders. In order to give full play to the submarine's good resistance and manoeuvrability, the SBD technique is used to optimize the shape of main hull. The six shape parameters of the main hull can be changed and regarded as optimization design variable, and the drag and tactical turning diameter are evaluated based on CFD. Furthermore, the Optimized Latin Hypercube Sampling method and Kriging surrogate model are adopted to save the computational cost. Then, the Multi-objective Constrained Particle Swarm Optimization algorithm is used to obtain the optimal hulls under several constraints. Finally, the applicable schemes for different working conditions are given.

KEY WORDS: Submarine; SBD technique; Resistance; Manoeuvrability; Hull form optimization; OLHS; MOCPSO.

INTRODUCTION

Submarine has incomparable navigation advantages underwater due to its good performances including resistance and manoeuvrability, and is widely used in military and civil fields. Since the main hull has a strong influence on the resistance and maneuverability of the submarine, the optimization of the main hull should be prioritized.

In the past, researchers often used the empirical mode of "modify-evaluate-re-modify-evaluate" for the optimization of hull form, but this mode has the disadvantages of low efficiency, poor accuracy, ambiguous direction and empirical dominance, which limit the optimization process to a certain extent. In order to overcome the limitations of this empirical mode, a simulation-based design (SBD) technique has been developed, which has the advantages of high efficiency, large design space and good optimization results. The SBD technique can be divided into five parts: hull form modification, design of experiment, hydrodynamic performance evaluation, surrogate model construction and optimization algorithm.

In the past decade, a lot of research has been conducted on the optimization of ship resistance, seakeeping and maneuverability using SBD technique. Hyunyul Kim and Chi Yang (2010) used KRISO container ship (KCS) as the initial hull and combined radial basis function interpolation and Lackenby's method to achieve local and global hull form modifications to optimize the total drag at different speeds. Li (2012) realized hull from modification by changing the cross-sectional area curve of the initial ship, and carried out multi-objective optimization for the speed, wave resistance and maneuverability of the ship. Bagheri, L., Ghassemi, H. and Dehghanian, A. (2014) used the S60 hull and the Wigley hull as the initial hull to optimize the peak vertical motion characteristics at different Fr and obtained the optimal ship with the displacement as the design constraint. Lin Y, Yang Q and Guan G (2019) established an automatic optimization platform based on the MIGA method in conjunction with the response surface methodology, and analyzed the hydrodynamic performance of the samples generated by the RSM through CFD calculations, and optimized the design for the resistance of the 2.7m SWATH model at Fr = 0.29. Liu, Wan and Hu (2021) used shifting and Radial Basis Function (RBF) methods to optimize Wigley ship based on calm-water wave drag with or without generating bulbous bow, the results show that the bulbous bow generation method proposed has potential for the drag optimization of medium and high-speed hulls.

Several advancements have been made to the optimization of submarine performance, and achieved good results. Qian and Liu (2011) used the dimensions and the longitudinal coordinates of the control surfaces are selected as the design variables, the unitary dimensional hydrodynamic coefficients were calculated and the submarine maneuverability prediction model was established. Based on the iSIGHT optimization platform, the Multi-objective optimization and Sensitivity analysis of the submarine maneuverability objects were carried out. Kou, Yin, Dong and Zhou (2013) came up with the idea of optimizing missile dome for the SUBOFF submarine based on CFD and iSIGHT optimization platform. With the optimization objective of minimizing the drag, the optimal missile dome design parameters are determined and the variation of the drag with each design parameter is analyzed. Mora Paz and Tascón Muñoz (2014) combined slender body theory, hull form parametric modeling, drag evaluation and optimization techniques to optimize the drag and radius of turning using the length and radius of hull, longitudinal position of the sail, area and aspect ratio of rudder as design variables. Deddy, Ahmad and Berlian (2015) used cubic Bezier curve and curve-plane intersection method for parametric submarine hull form design to optimize hull resistance. Wu, Lin, Liu and Su (2020) proposed to improve the maneuverability of lifting and diving for underwater vehicle's vertical motion by optimizing the L/D, the position of the foreplane and sail to obtain a robust design.

In this Study, the SUBOFF model is considered as the initial hull. The hull form can be globally deformed by the improved shifting method which is based on the translation of section planes along the longitudinal direction. The multi-objective constrained particle swarm optimization (MOCPSO) algorithm is taken as optimization technique leading to three optimal submarine model considering the surface resistance, underwater resistance and tactical turning diameter. All the sample points are generated by the Optimal Latin Hypercube Sampling (OLHS) method and their resistances and tactical turning diameters are evaluated by RANS-based CFD solver STAR-CCM+. After doing the optimization through MOCPSO combined with Kriging surrogate model, three optimization cases will be given. The whole optimization process is implemented using the in-house ship hull optimization platform based on Python language.

OPTIMIZATION THEORIES

Hull Form Modification

Hull form modification is an important part of SBD technique, which determines the deformation pattern of the hull during the optimization process. The hull form modification can be broadly classified into two categories based on ship form parameters and geometric parameter. When choosing the modification method, the focus should be on the design requirements and features suitable for the optimized ship, and the design space should be as large as possible by using as few design variables as possible. Since the main emphasis of this study is on how globally modification of the hull form of SUBOFF affect the resistance and manoeuvrability, the shifting method are utilized to generate new ship form based on design variables.

The shifting method was first proposed by Lackenby (1950), and was extended with various forms. In the early shifting method, the hull modification is controlled by the section area curve which is a quadratic polynomial consisting of the prismatic coefficient, longitudinal center of buoyancy and parallel midbody position. Although the curve can be approximated to a certain extent, the hull form can only be modified by the above variables. Kim, Yang and Noblesse (2010) proposed to describe the section curve by spline polynomials, the new formulation consists of four variables that control the slope of the sectional area curve, the location of fixed station and the shifting range, this approach improves some flexibility, but still does not provide sufficient control over the section curve.

In the present study, the section area modification curves constructed by B-Spline curves (Piegl, Les and Tiller, Wayne, 1997), which can control both the position and size of the modified function and the curvature of the fore and after part of the modified function are applied to the original hull section area curves (SAC), and then the new section area curves are used to obtain the new hull. The new formulation has been applied as follows:

$$f^n(x) = f^0(x) + g(\Delta x_0, \Delta x_1, \Delta\alpha_0, \Delta\alpha_1), \quad x_0 \le x \le x_1 \qquad (1)$$

where $f^n(x)$ denotes the new sectional area curve, $f^0(x)$ represents the initial sectional area curve, $g(\Delta x_0, \Delta x_1, \Delta\alpha_0, \Delta\alpha_1)$ is a B-spline curve, which represents the modified function, x_0 and x_1 represent the start and end points of the shifting range in x direction, Δx_0 and Δx_1 represent the position of the each end of curve, $\Delta\alpha_0$ and $\Delta\alpha_1$ represent the tangent angle of the each end of curve. Table 1 shows the variables for SAC modified function of run part and entrance part, the SAC of the initial hull and deformed hull is shown in Fig. 1.

Table 1. Variables for SAC modified function

	Run part		Entrance Part	
	Beginning x_{0R}	End x_{1R}	Beginning x_{0E}	End x_{1E}
Position	Δx_{0R}	Δx_{1R}	Δx_{0E}	Δx_{1E}
Tangent angle	$\Delta\alpha_{0R}$	$\Delta\alpha_{1R}$	$\Delta\alpha_{0E}$	$\Delta\alpha_{1E}$

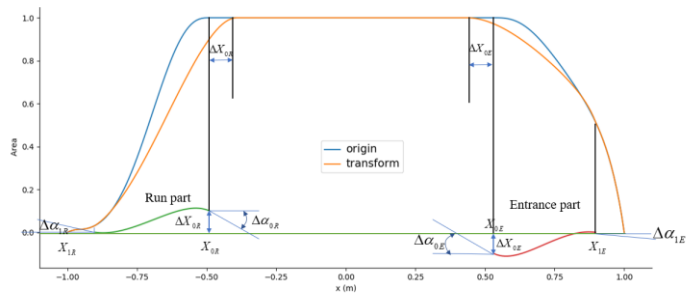


Fig. 1 SAC comparison of the original and deformed hulls

Design of Experiment

In order to save the computational cost, the surrogate model will be built, before which the sample points need to be selected reasonably. The sample points can be obtained by the design of experiment, and an excellent design method can effectively reduce the number of simulation calculations.

The Latin Hypercube Sampling (LHS) design method was proposed in 1979 (Mckay M D, Beckman R J, Conover W J). LHS can sample points uniformly and randomly in the design space. The value range of each variable $X = (x_1, \cdots x_n)$ is divided equally into n parts, after which the $n+1$ levels of each of these variables are arranged in random combinations to generate n+1 sample points, and each level of each variable is guaranteed to be used only once. Fig.2 gives the example of the sample points with 2 variables and 9 levels.

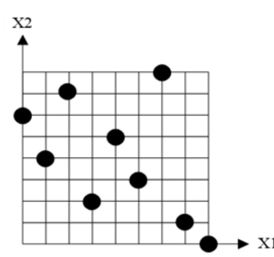


Fig.2 The sample points with 2 variables and 9 levels

Although the Latin Hypercube Sampling is able to provide full coverage of the range of variables, it lacks uniformity and orthogonality in the design space for the distribution of sample points, and it is difficult to ensure the robustness of sampling quality with randomly combination. To address the shortcomings of LHS, Thomas M C (2002) and Morris M D, Mitchell T J (1995) improved the orthogonality and uniformity of the LHS, respectively, on the basis of which this study will improve the LHS using simulated annealing algorithm (Liu, Chen, Jin, Chen, 2011) to ensure that the sampling points are uniformly distributed throughout the design space, while taking into account the orthogonality so that the collection of experimental case can be a representative subset of the points in the hypercube of explanatory variables.

Uniformity of design matrix is first studied. Fang, Lin, Winker and Zhang (2000) define a uniform design as one in which the sampling points are evenly distributed throughout the entire experimental region. The criterion used to measure the uniformity of the design matrix is the “Minimax and Maximin distance design” proposed by Johnson, Moore, Ylvisaker (1990).

In this paper, the distance between two sample points, i.e., the distance between each column in the design matrix, is defined as Euclidean distance:

$$d(x_i, x_j) = d_{ij} = \left[\sum_{k=1}^{m}(x_{ik} - x_{jk})^2\right]^{1/2}, 1 \le i, j \le m, i \ne j \tag{2}$$

where x_{ik} and x_{jk} denote the level values on different columns of the design matrix.

For a given design D, define a distance list $d = (d_1, d_2, \cdots, d_m)$ in which the element are the distinct values of distance, sorted from the smallest to the largest. Also, define an index list $J = (J_1, J_2, \cdots J_m)$, in which J_i is the number of pairs of points whose distance satisfies d_i.

In the following, in order to obtain a design criterion function with scalar values that can be used to obtain the distance characteristics between sampling points in design space, “Minimax and Maximin distance design (Mm)” criterion is introduced as follow:

$$\varphi_p = \min[\sum_{i=1}^{s} J_i d_i^{-p}]^{1/p} \tag{3}$$

where p is a positive integer, for large enough p, each term in the sum in Eq. 3 dominates all subsequent terms, and so from any design class, the design that minimize φ are the Mm designs in that class, we take $p = 15$. J_i and d_i characterize the design D.

Next, orthogonality of design matrix is discussed. Orthogonality is used to ensure independence among the coefficient estimates in a regression model. Ye (1998) construct orthogonal Latin hypercubes (OLHC) to enhance the utility of Latin hypercube designs for regression analysis, which is zero correlation for every pair of columns. In order to measure the degree of orthogonality, the maximum pairwise correlation of the columns of a design matrix is used.

The correlation between two columns in a design matrix:

$$\rho_{ij} = \frac{\sum_{b=1}^{n}\left[(x_b^i - \overline{x^i})(x_b^j - \overline{x^j})\right]}{\sqrt{\sum_{b=1}^{n}(x_b^i - \overline{x^i})^2 \sum_{b=1}^{n}(x_b^j - \overline{x^j})^2}} \tag{4}$$

The maximum pairwise correlation of the columns measures the two most correlated columns in the matrix, that is:

$$\rho_{\max} = \max_{i \ne j}\left\{\left|\rho_{ij}\right|\right\} \tag{5}$$

A value of 0 is the best (signaling orthogonality), and a value of 1 is worst (at least one column is a linear combination of the remaining columns), a design matrix will be classified as nearly orthogonal if it has a maximum pairwise correlation no greater than 0.03. Thus, by minimizing $\rho_{\max}$ it is possible to control the correlation between columns to achieve nearly orthogonality.

In order to create new designs that perform well in both orthogonality and uniformity, i.e., Optimal Latin Hypercube Sampling (OLHS), this study uses the simulated annealing (SA) algorithm to optimize orthogonality and uniformity on the basis of LHS. To reduce the burden of the SA algorithm as well as the time cost, an initial design matrix with good orthogonality is created using the Florian (1992) method.

Firstly, a Latin Hypercube matrix R is generated, each column R of is replaced with the element’s rank ($1, 2, ..., n$), within the column. Let T_{ij} represent the Spearman rank correlation matrix of R:

$$T_{ij} = 1 - \frac{6\sum_{i=1}^{n}(R_l^i - R_l^j)^2}{n(n^2 - 1)} \tag{6}$$

The basic idea is to transform T_{ij} into a set of uncorrelated variates. A Cholesky factorization scheme is used (since T_{ij} is positive definite) to determine a lower triangular matrix L. Then, let $S = Q^{-1}$ and $T = QQ^T$ such that S has the property:

$$STS^T = I \tag{7}$$

The original R is then transformed into a new matrix R_{new}:

$$R_{new} = RS^T \tag{8}$$

Since the element of the matrix R_{new} are not necessarily integral, the elements in each column are replaced by their rank order ($1, 2, ..., n$), this process can be repeated. We do so until there is no further decrease in the maximum pairwise correlation. Finally, to reconstruct the Latin hypercube design matrix, the ordered rank in the final R_{new}, i.e. R_{LHD} are then mapped back into the original input variable values. In addition, in order to eliminate the effects of differences in the magnitude and range of values of different variables, the Z-Score shown in Eq. 9 needs to be applied to R_{LHD}, mapping each row of the matrix to standard data with a mean of 0 and a standard deviation of 1.

$$x^* = \frac{x - \overline{x}}{\sigma} \tag{9}$$

The OLHS is implemented on the basis of the Simulated Annealing (SA) algorithm, which generates new design matrix by column transformation. Because SA algorithm is sensitive to the choice of the initial solution, so the matrix with good orthogonality R_{LHD} is used as the initial solution for the OLHS, and the optimization criterion ψ is defined by combining Eq. 3 and Eq. 4.

$$\begin{aligned} \min\ \psi &= (1-\omega)\rho_{\max} + \omega\varphi \\ \omega &= 1 - n/2N \end{aligned} \tag{10}$$

where $\rho_{\max}$ is the maximum pairwise correlation of the columns, φ is the Mm criterion, ω is weight coefficient, n is the number of current iterations, N is the total number of iterations.

In the initial stage of the SA algorithm, more weights are given to φ in order to optimize the matrix uniformity, and later in the iteration to ensure that the matrix orthogonality does not degrade, the weights are increased toward $\rho_{\max}$, and finally $\omega = 0.5$ ensures that both criteria are equally important.

Optimization Algorithm

The optimization algorithm performs the task of finding the optimal design in SBD technology. Since there may be more than one objective function in the optimization scheme, multi-objective optimization algorithms will be employed. In this study, the Multi-objective Particle Swarm Optimization (MOPSO) algorithm is chosen as the optimization algorithm. Besides, the constraint problem will be involved in the ship optimization process, so the Multi-objective Constrained Particle Swarm Optimization (MOCPSO) algorithm will be investigated.

For multi-objective optimization problems, for non-dominated solutions that will be included in the Pareto optimal set, where the solution is unable to improve one of the objective values without weakening the other, thus at the end of the optimization we get a Pareto front, i.e., a set of optimal solutions. The detail of the theory of the MOPSO can be found in the reference related (Coello, Pulido and Lechuga, 2004). On this basis, the inertia weight and learning factors involved in the optimization process are modified in this study, and the mutation operator is added to make the algorithm easier to avoid local optimal in global optimization.

In order to enhance the algorithm's search capability, dynamic parameters are used in the algorithm to set the inertia weights ω and learning factors c_1 、 c_2 in the velocity update formula (Eq. 11), according to Eqs. 12-14. The intention is to make the algorithm focus on global search (a social component) in the early stages and on individual search (a cognitive component) in the later stages, i.e., to search in the entire design space as much as possible in the early stages and to search more in the vicinity of the current optimal solution in the later stages to improve the accuracy.

$$v_{id}^{k} = \omega v_{id}^{k-1} + c_1 r_1 (p_{id} - x_{id}^{k-1}) + c_2 r_2 (g_{id} - x_{id}^{k-1}) \tag{11}$$

$$\omega = 0.9 - 0.4 \times (2 \times \frac{t+1}{N} - (\frac{t+1}{N})^2) \tag{12}$$

$$c_1 = 0.5 \times \omega^2 + 3 \times \omega \tag{13}$$

$$c_2 = 4 - c_1 \tag{14}$$

where v_{id}^{k} denotes the d -th component of the velocity of the i -th particle at the k -th iteration, p_{id} denotes the optimal position in dimension d searched by the i -th particle, g_{id} denotes the optimal position in dimension d searched by the population. c_1 and c_2 are random numbers in the range $[0,1]$, t is the number of current iterations, N is the total number of iterations.

In addition, to enrich the exploratory capability of the algorithm, the mutation operator is incorporated into the algorithm, and the mutation operator will try to explore with all the particles at the beginning of the search to fully search the design space, while decreasing the number of particles that affected by the mutation operator in the later stage to prevent weakening the optimal solutions already searched. The mutation rate is linearly reduced from 0.9 to 0.05 by Eq. 15, and all particles in the population are assigned a random number p_m . If p_m is less than the mutation rate, the mutation is performed at a random position of the particle according to Eq. 16.

$$Pmutation = 0.9 - (0.85/N) \times t \tag{15}$$

$$x_{id}^{k} = random(-1,1) \times p_m \times \theta \times v_{id}^{k-1} + x_{id}^{k} \tag{16}$$

where $Pmutation$ denotes the mutation rate, θ is the parameter that accelerates the moving speed of particle, we take $\theta = 3$

In this study, the constrained optimization problem will be solved by using the penalty function method, and the algorithm will become the Multi-Objective Constrained Particle Swarm Optimization (MOCPSO) algorithm. The objective function will consist of an original objective function, a penalty function and a penalty factor.

The constrained optimization problem is defined as:

$$\begin{cases} \min f(x) \\ s.t.\ g_i(x) \ge 0,\ i = 1, \cdots, m \end{cases} \tag{17}$$

The penalty function method transforms the objective function into:

$$\min F(x) = f(x) + \sigma \sum_{i=1}^{m} [\max\{0, -g_i(x)\}]^2 \tag{18}$$

where $f(x)$ denotes the original objective function, σ is the penalty factor, $g_i(x)$ denotes the constraints.

Hydrodynamic Performance Evaluation

Hydrodynamic performance evaluation plays an important part in the SBD technique. After obtaining sample points through OLHS, the commercial CFD program, STAR-CCM+ is used to evaluate the resistance and maneuverability of the submarine.

The governing equations is Reynolds-averaged Navier-Stokes(RANS) equations, and $K-Epsilon$ model and SST $\mathrm{k}-\omega$ model were selected as the turbulence model for surface and underwater simulation respectively. DFBI (Dynamic Fluid Body Interaction) was used for the motions of the SUBOFF with rudders. We can get pressure distribution of the hull, resistance of the hull, wave height along the hull and wave elevation of the free surface, etc.

In order to prove the accuracy of the CFD computations, we compared the CFD results of submerged resistance evaluation with the experimental results (Huang and Liu, 1998), as shown in Table 2.

Table 2 Comparison of CFD and experimental resistance results

Model speed $V_m / m{\bullet}s^{-1}$	CFD /N	Experiment /N	Error /%
3.051	102.30	102.3	0
5.144	280.56	283.8	1.14
6.096	382.46	389.2	1.73
7.161	523.86	526.6	0.52
8.231	675.94	675.6	0.05
9.152	820.11	821.1	0.12

As can be seen from the Table 2, the error of CFD simulation results compared with the experiment are less than 2%, which is enough to prove the accuracy of CFD computations.

Surrogate Model Construction

After the design of experiment and hydrodynamic performance evaluation are completed, the surrogate model can be constructed, which can save the computational cost. The surrogate model can replace the hydrodynamic evaluations required for each iteration of the optimization algorithm by finding a strong nonlinear relationship between the design variables (input) and the objective function (output).

The Kriging model is an unbiased estimation model that minimizes the estimation variance, which has high prediction accuracy for highly nonlinear problems and guarantees that the predicted values pass through the sample points. In this study, the Kriging model will be chosen as the surrogate model, the main idea of Kriging model can be seen in the article of Liu, Wang, and Wan (2018).

HULL FORM OPTIMIZATION CASE

Objective Function

The initial ship used in this paper is SUBOFF model of the Defense Advanced Research Projects Agency (DARPA) SUBOFF project, the model includes an axisymmetric body, fairwater, symmetric stern appendages, whose two views are given in Fig. 3, and the main dimension of the model are listed in Table 3.

Table 3. Main dimensions of SUBOFF model

Overall Length L_{OA} /m	4.356	Forebody Length L_{fore} /m	1.016
Parallel Middle Body Length L_{pal} /m	2.229	Afterbody Length L_{aft} /m	1.111
Maximum Body Diameter Δx_{0R} /m	0.508	Stern appendages locations Δx_{0R} /m	4.007
Wetted Area Δx_{0R} /m^2	5.989	Volume Δx_{0R} /m^3	0.699

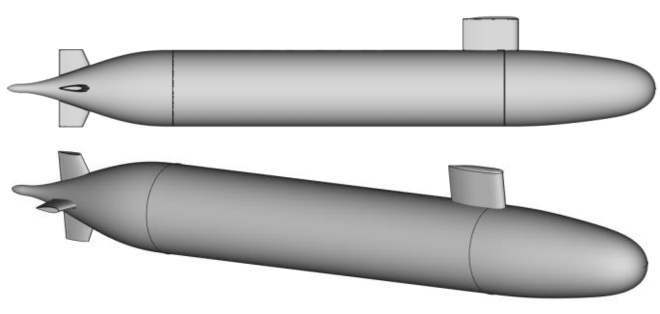


Fig. 3 Two views of SUBOFF

In this paper, we discuss the surface and underwater resistance of the SUBOFF model as well as the tactical turning diameter underwater, thus the objective functions and the constrains of the optimization problem are shown in Eq. 19.

$$
\begin{aligned}
&\min\begin{cases} f_1(x)=\min\{R_t\_suf\},V_m=1.050m/s \\ f_2(x)=\min\{R_t\_sub\},V_m=6.096m/s \\ f_3(x)=\min\{D_T\},V_m=3.05m/s,\delta=10^\circ \end{cases} \\
&constraints\begin{cases} -1\% \le \dfrac{\Delta^{'}-\Delta}{\Delta} \le 1\% \\ -1\% \le \dfrac{LCB^{'}-LCB}{LCB} \le 1\% \end{cases}
\end{aligned} \tag{19}
$$

where R_t_suf and R_t_sub denote the surface and underwater resistance respectively, D_T represents the tactical turning diameter, δ is the rudder angle, $\Delta^{'}$ and Δ denote the displacement of initial and optimal model respectively, $LCB^{'}$ and LCB denote the longitudinal center of buoyancy of initial and optimal model respectively.

Design Variables and Hull Form Deformation

From the theory of hull form deformation above, we need to identify eight design variables and four fixed variables. To ensure the smoothness of the SAC and the model, the Δx_{1R} and Δx_{1E} are set to zero. The twelve variables are listed in Table 4.

Table 4. Optimization design variables

	Run part		Entrance Part	
	Beginning x_{0R} /m	End x_{1R} /m	Beginning x_{0E} /m	End x_{1E} /m
	3.245	4.138	1.016	0.218
Position	Δx_{0R} /m	Δx_{1R} /m	Δx_{0E} /m	Δx_{1E} /m
Range	$[-5\%,5\%]\ L_{OA}$	0	$[-5\%,5\%]\ L_{OA}$	0
Tangent angle	$\Delta\alpha_{0R}$ /°	$\Delta\alpha_{1R}$ /°	$\Delta\alpha_{0E}$ /°	$\Delta\alpha_{1E}$ /°
Range	$[-30,30]$	$[-10,10]$	$[-30,30]$	$[-10,10]$

Note: The origin of the coordinate system is located at the end of the bow.

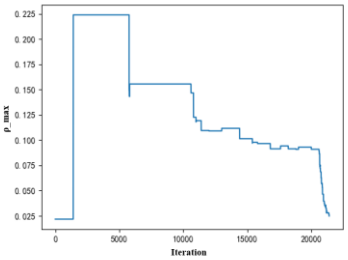
Design of Experiment

Based on the theory of OLHS above, 50 sample points with 6 design variables (design variables have been normalized to avoid the influence of different dimensions) were generated for 50 new hull form which are uniformly distributed in the design space at first. And then the orthogonality and uniformity of design matrix were optimized by using the simulated annealing (SA) algorithm. The optimized values of the four criterions set for design matrix are shown in Table 5, and the optimization process of the four criterions values is shown in Fig. 4.

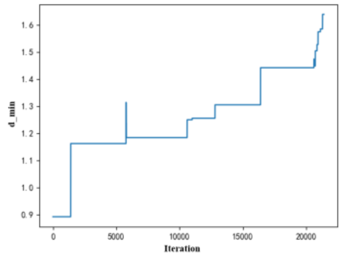
As can be seen from the Table 5, the maximum pairwise correlation of the columns $\rho_{\max}$ has been lower than 0.03 after the initialization of matrix with good orthogonality and reduced by 0.003 after optimization, so it has met the requirement of near-orthogonality ($\rho_{\max} \le 0.03$); the minimal distance between test points $d_{\min}$ has increased by 83.7%, so the uniformity criterion has been reduced by 36.6%. Finally, the optimization criterion ψ has been reduced by 34.3%.

Table 5 The initial and optimized criterions

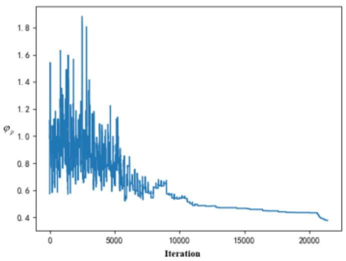
Criterion	Initial	Optimized
$\rho_{\max}$	0.028	0.025
$d_{\min}$	0.892	1.639
φ_p	0.574	0.364
ψ	0.574	0.377



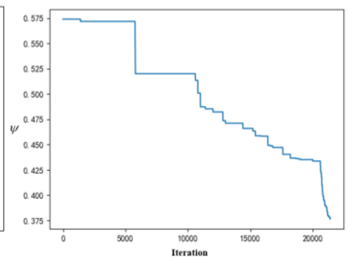
(a) Optimization of $\rho_{\max}$



(b) Optimization of $d_{\min}$



(c) Optimization of φ_p



(d) Optimization of ψ

Fig. 4 The optimization process of the criterions

Optimization Results and Analysis

After evaluating the hydrodynamic performance of the new hull forms for resistance and maneuverability, the Kriging surrogate model can be constructed. The results for the 50 new hull forms are shown in Figs. 5~7, the green straight line represents the baseline design result, and all the sample values show in the fig.5-7 are only used to build the Kriging surrogate model..

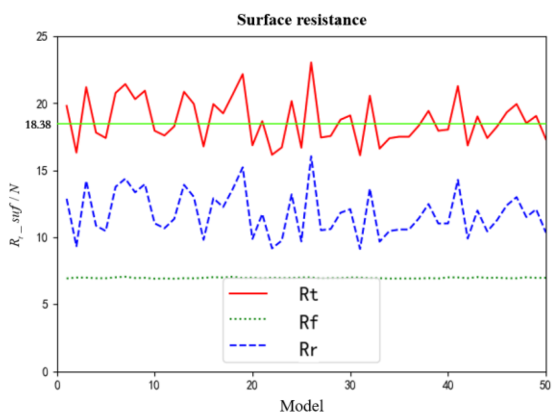


Fig.5 Surface resistance of 50 new hull forms

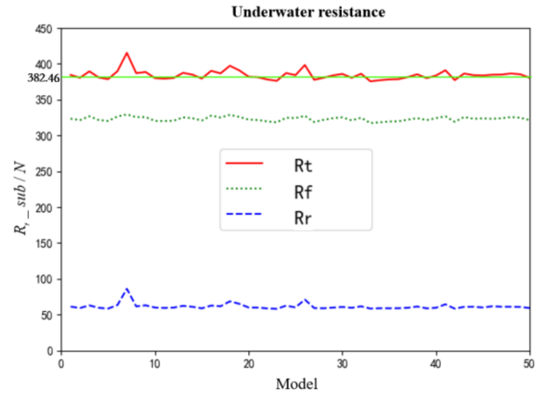


Fig.6 Underwater resistance of 50 new hull forms

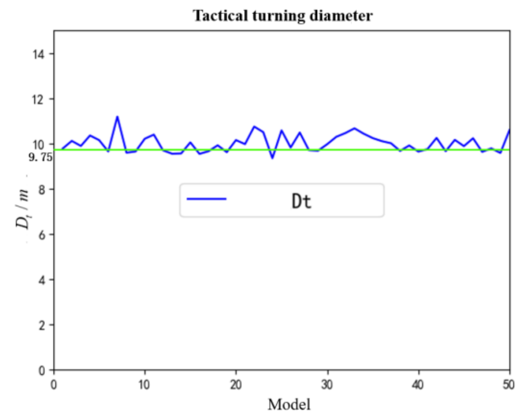


Fig. 7 Tactical turning diameter of 50 new hull forms

After construction of Kriging surrogate model, the MOCPSO algorithm can be used to optimize the resistance and manoeuvrability of SUBOFF model. The parameters of the MOCPSO are shown in Table 6, the pareto front is shown in Fig.8.

Table 6 The parameters of MOCPSO

Learning factor c_1	2.0	Learning factor c_2	2.0
Max Inertia weight $\omega_{\max}$	0.9	Min Inertia weight $\omega_{\min}$	0.4
Number of iterations $k_{\max}$	500	Particles number M	100
Number of grid subdivisions	10	Pareto set threshold	100

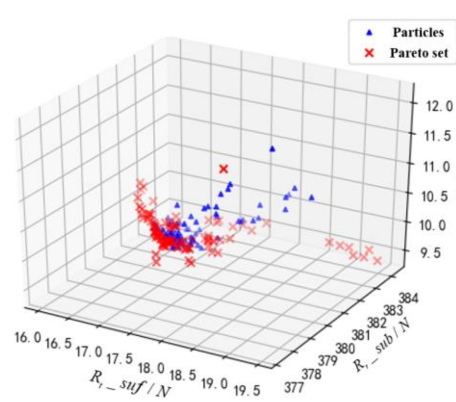


Fig. 8 Pareto front

Three typical optimal hulls are selected from the Pareto front for different principles, and their design variables are shown in Table 7, the comparisons of resistance and tactical turning diameter between initial and optimal hull forms are shown in Table 8. The wave elevations and underwater pressure distribution of initial and optimal hull form are shown in Fig. 9~10. In addition, the optimization results are all come from changes to the baseline suboff model.

Table 7 Design variables of the optimal hull

Design variables	Range	Opt 1	Opt 2	Opt 3
ΔX_{0R}	[-0.2178, 0.2178]	0.120	0.176	-0.083
ΔX_{0E}	[-0.2178, 0.2178]	0.216	-0.087	-0.022
$\Delta\alpha_{1R}$	[-10, 10]	-7.3	-0.57	-0.55
$\Delta\alpha_{0R}$	[-30, 30]	9.9	15.5	-15.28
$\Delta\alpha_{0E}$	[-30, 30]	-17.1	2.61	0.71
$\Delta\alpha_{1E}$	[-10, 10]	-8.1	0.12	3.21

Table 8 Comparison of resistance and tactical turning diameter

		Initial	Opt 1	Opt 2	Opt 3
R_t_suf	Value /N	18.38	15.89	17.36	19.5
	ΔR_t_suf	/	-13.50%	-5.50%	+6.09%
R_t_sub	Value /N	382.46	383.34	378.33	384.2
	ΔR_t_sub	/	-0.20%	-1.10%	+0.50%
D_T	Value /m	9.748	10.13	10.13	9.64
	ΔD_T	/	+3.92%	+3.92%	-1.11%

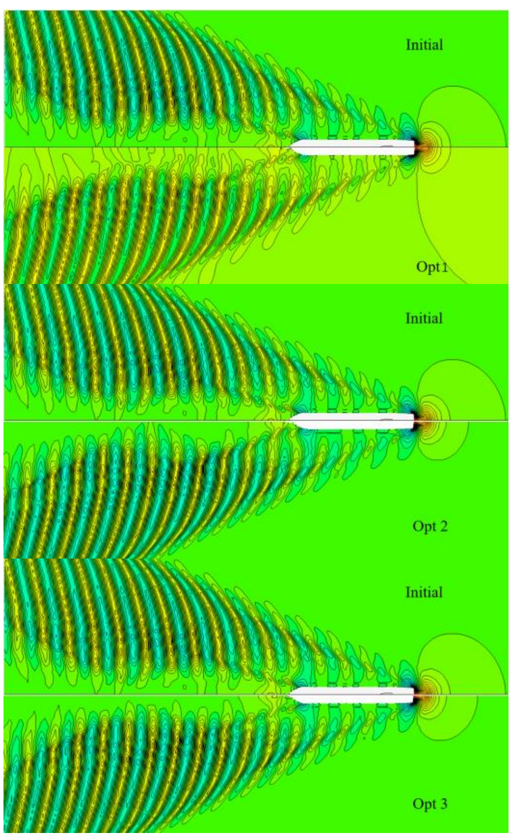


Fig. 9 Comparison of wave elevations

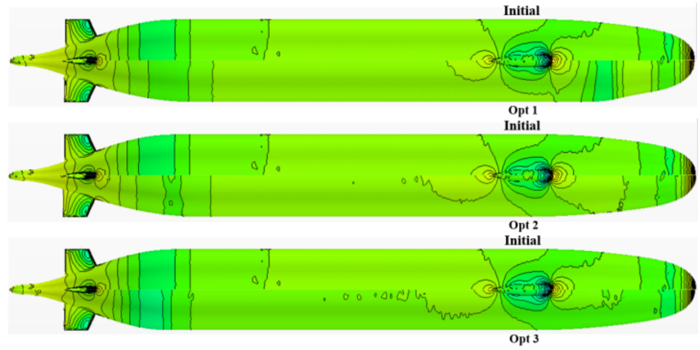


Fig. 10 Comparison of underwater pressure distribution

As can be seen from the results, the Opt 1 hull has the best surface resistance performance, the Opt 2 hull has a largest decrease of the underwater resistance, but these two optimal hulls have poor performance in maneuverability. On the contrary, the Opt 3 hull have the smallest tactical turning diameter but does not perform well in resistance. The hydrodynamic performance of the above three optimal hull is consistent with what we know about the inconsistent optimization trend of resistance and maneuverability. Therefore, a comprehensive objective function design for different requirements is needed in the submarine design.

CONCLUSIONS

The SUBOFF submarine model is adopted as the initial hull form whose objective function are the surface resistance, underwater resistance and tactical turning diameter. The shifting method are utilized to generate new hull form based on design variables, the sample points with good orthogonality and uniformity are obtained by using Optimal Latin Hypercube Sampling method. After evaluating the hydrodynamic performance of samples, the Kriging model is constructed. Finally, the Multi-objective Constrained Particle Swarm Optimization algorithm is used to get the Pareto front, three typical optimal hull forms are selected, and show that different requirement for resistance and maneuverability will influence optimal trend to a great extent, which provides a reference for future submarine design work.

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