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Wigley Hull Design Optimization Based on Artificial Neural Network and Genetic Algorithm

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ABSTRACT

To improve the ship hull optimization efficiency and take full advantage of the non-linear fitting capability of neural networks and the fast random search capability of genetic algorithms, the Wigley hull optimization based on artificial network and genetic algorithm is investigated in the present paper. The in-house hull form optimization software OPTShip-SJTU is firstly applied to obtain a series of new hull form and to calculate these hull resistances. Then a surrogate model of 3-layer BP neural network is constructed based on the sample data and a genetic algorithm is used to optimize the design of the Wigley ship with the total resistance minimum as the optimization objective function. During the calculation of hull hydrodynamics, potential flow solver NMShip-SJTU combined with ITTC formula is adopted to efficiently obtain the total resistance of the Wigley hull. The verification is also carried out to ensure the reliability of the optimization result. The results show that the resistance performance of the Wigley hull can be improved by designing the hull form reasonably. Besides, the form of bow bulbous is essential for the decreasing of total resistance according to the parameters sensitivity analysis. The design method—artificial network and the genetic algorithm can accurately work out the minimum resistance hull form and can be taken as a practical and efficient design tool.

KEY WORDS: hull form optimization; neural network; surrogate model; genetic algorithm;

INTRODUCTION

With the implementation of the green ship and Ship Energy Efficiency Design Index (EEDI), how to reduce fuel consumption and carbon emission becomes the focus of the attention of shipyards and ship owners. One way to alleviate this problem is to optimize ship-shape curves. Based on the original ship, the ship-shape curves are optimized to reduce the wave-making resistance of the hull, and the ship-shape line also can be optimized with multiple objectives considering the ship's 6-DOF motion index.

The method of combining neural networks and genetic algorithm is used widely in different fields. Wang, Han, Sun, and Guo (2020) combined the elliptic basis (EBF) neural network approximation model and genetic algorithm to optimize the KP505 propeller, obtained the optimal design scheme theoretically and improved the optimization efficiency. Zeng, Ding, and Tang (2010) used the BP neural network and genetic algorithm to establish a new method for the optimal design of ship propeller based on the original map design method. Koushan (2003) used the genetic algorithm and neural networks to optimize the resistance and wave-making of a high-speed ship, and the optimization effect was obvious. Xu, Zhou, and Wang (2017) used the neural networks and genetic algorithm to optimize the ship's mooring system, and the optimization result is well. Yan, Liu, Xu, and Feng (2013) used the BP neural network and genetic algorithm to obtain the seaworthiness layout of trimaran ships with different layouts at different speeds. Wang, Lu, and Wang (2020) applied neural network and genetic algorithm to the airfoil optimization, optimized FFAW3-301 airfoil have better aerodynamic performance. The optimization results showed that the optimization method was feasible. Lv, and Wang (2018) use the RBF neural network and genetic algorithm to optimize the strength of the ship hull after the broken. Chen and Ye (2009) firstly used the genetic algorithm to optimize the weights of the neural network, and then used the optimized neural network to predict the resistance of series 60 ship types. The neural network is simple and fast to calculate the resistance of ships, which can be applied to the calculation of ship resistance. Lin, Chen, Luo, and Wang (2019) analyzed a large number of data collected during the operation of a bulk cargo ship and used BP artificial neural network for training under the condition of considering fuel consumption. The fuel consumption rate optimization model is based on the neural network and the genetic algorithm is established. Xu (2012) used the BP neural network to optimize the layout of the trimaran with static water resistance as the target. From above all, we can realize that the BP neural network surrogate model is applied in optimization. But for hull optimization, it doesn't been applied for the wide hull.

In this paper, a 4 m Wigley hull is considered as the initial ship. The total resistance of the Wigley hull is optimized in calm water when Fr=0.3. The original Wigley hull was deformed by in-house software OPTShip-SJTU using shifting method and RBF (Radial Basis Function) method, and the deformation of Wilgley hull be controlled by 7 parameters. In-house potential solver NMShip-SJTU is used to calculate the wave-making resistance coefficient, and combined with the ITTC formula, the total resistance can be obtained fast. Then a 3-layer BP neural network surrogate is established and a genetic algorithm is used to get the best hull deformation parameters based on the BP neural network surrogate model. After obtaining the optimized Wigley hull, NMShip-SJTU is applied to validate the result of optimization.

OPTIMIZATION THEORIES

Hull Form Modification

Hull form modification is one of the most important periods during the hull form optimization. The quality of hull form modification directly affects the hydrodynamic calculation results and optimization of hull hydrodynamic performance. The common methods used hull form modification include Shifting Method, Radial Basis Function (RBF), Free-Form Deformation, etc. The Radial Basis Function method and Shifting method are used in this paper which is briefly introduced below. For the Wigley in the present paper, the Shifting method is used to deform the first half of the Wigley, and the Shifting method is also used to deform the second half of the Wigley, the RBF method is used to deform the bow bulbous, Tthe RBF method changes the shape of the ship by moving the control points on hull surface. And the Shifting method changes the shape of the ship by modifying the transverse section curves.

The Radial Basis Function (RBF) is a class of functions related to the Euclidean distance, it can usually be written as:

$$\phi\left(\left\|x-x_i\right\|\right), \qquad i=1,2,\cdots,n \tag{1}$$

where x is the independent variable, represents any point in space. While x_i is the central symmetric point of radial basis function. Given a set of data $\{x_i, f_i\}, i=1,....,n$, using linear combinations of radial basis functions, as shown below:

$$S(x)=\sum_{j=1}^{n}\lambda_i\phi\left(\left\|x-x_i\right\|\right) \tag{2}$$

Interpolation fitting is adopted. $S(x)$ satisfied the following interpolation conditions:

$$S(x)=f_i, \quad i=1,2,....,n \tag{3}$$

Where λ_i is the interpolation coefficient, basis function $\phi\left(\left\|x-x_i\right\|\right)$ is equivalent to a basis for a higher-dimensional space. According to equation(3), we can obtain the linear equation about λ_i:

$$\begin{bmatrix} \phi_{11}\cdots\phi_{1i}\cdots\phi_{1n} \\ \vdots\ \ \vdots\ \ \vdots\ \ \vdots\ \ \vdots \\ \phi_{i1}\cdots\phi_{ii}\cdots\phi_{in} \\ \vdots\ \ \vdots\ \ \vdots\ \ \vdots\ \ \vdots \\ \phi_{n1}\cdots\phi_{ni}\cdots\phi_{nn} \end{bmatrix}\begin{bmatrix}\lambda_1\\ \vdots \\ \lambda_i \\ \vdots \\ \lambda_n\end{bmatrix}=\begin{bmatrix}f_1\\ \vdots \\ f_i \\ \vdots \\ f_n\end{bmatrix} \tag{4}$$

Where $\phi_{ij}=\phi\left(\left\|x_i-x_j\right\|\right), \quad i,j=1,2,\cdots,n$. To guarantee the unique solution of the linear equations, the following conditions should be satisfied: the coefficient matrix is a positive definite matrix (the same interpolation points do not exist in $\{x_i, f_i\}$).

In the hull surface deformation based on the radial basis function interpolation method, the interpolation function takes the following form:

$$s(\mathbf{x})=\sum_{j=1}^{N}\lambda_j\phi\left(\left\|\mathbf{x}-\mathbf{x}_j\right\|\right)+p(\mathbf{x}) \tag{5}$$

Where $\mathbf{x}_j$ represents the RBF control point coordinates. $s(\mathbf{x})$ Represents the coordinate value after the control point moves. N represents the number of control points of RBF, $\left\|\mathbf{x}-\mathbf{x}_j\right\|$ represents the Euclidian distance between two points, and $p(\mathbf{X})$ is a low-order polynomial of radiological transformation:

$$p(\mathbf{X})=c_1+c_2x+c_3y+c_4z \tag{6}$$

ϕ is the Radial Basis Function, which has various forms. This paper selects the Compact Support Radial Basis Function (CSRBF) Wendland $\psi_{3,1}$ Radial Basis Function.

$$\phi\left(\left\|X\right\|\right)=\begin{cases}\left(1-\left\|X\right\|/r\right)^4\left(4\left\|X\right\|/r+1\right) & 0\le\left\|X\right\|\le r \\ 0 & \left\|X\right\|>r\end{cases} \tag{7}$$

Where r represents the support radius. According to equation (7), when the Euclidean distance between any control point $\mathbf{X}$ and the center point $\mathbf{x}_j$ is bigger than the support radius r, the movement of $\mathbf{x}_j$ does not have any influence on the $\mathbf{X}$. On the contrary, it will be affected, and the distance is smaller, the impact is the greater.

According to interpolation condition (3) and additional conditions:

$$\sum_{j=1}^{n}\lambda_j p\left(\mathbf{X}_j\right)=0 \quad , \quad j=1,2,\ldots,n \tag{8}$$

The following equations can be obtained:

$$\begin{pmatrix} f \\ 0 \end{pmatrix}=\begin{pmatrix}\boldsymbol{M} & \boldsymbol{q} \\ \boldsymbol{q}^{\boldsymbol{T}} & \boldsymbol{0}\end{pmatrix}\begin{pmatrix}\boldsymbol{\lambda} \\ \boldsymbol{c}\end{pmatrix} \tag{9}$$

In the formula:

$$\boldsymbol{\lambda}=[\lambda_1,\lambda_2,\cdots\lambda_n]^T \tag{10}$$

$$\boldsymbol{c}=[c_1,c_2,c_3,c_4]^T \tag{11}$$

$$\boldsymbol{f}=[f_1,f_2,\cdots,f_n]^T \tag{12}$$

$$M_{i,j}=\phi\left(\left\|\boldsymbol{X}_i-\boldsymbol{X}_j\right\|\right), \quad i,j=1,2,\cdots,n \tag{13}$$

$$q=\begin{bmatrix}1 & x_1 & y_1 & z_1 \\ 1 & x_2 & y_2 & z_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_n & y_n & z_n\end{bmatrix} \tag{14}$$

When this method is applied in the hull form modification. firstly, all the control points of the hull surface are divided into three categories:

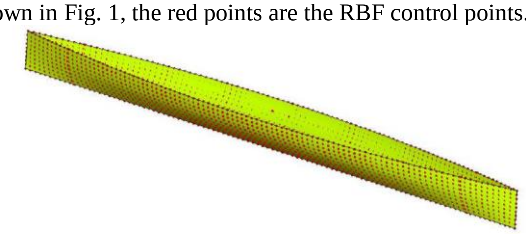
(1) Fixed control points: Fixed and stationary nodes usually fall on the feature line of the hull, such as the design waterline, the middle longitudinal section line, and the middle transverse section line;

(2) Movement control points: nodes that are controlled by

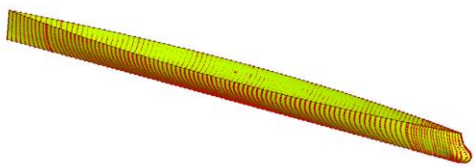
optimized design parameters;

(3) Other nodes that change with the movement of control points.

The method involves fewer design variables when deforming the hull surface, and the changes are flexible, the design variables are intuitive and the deforming is easy to control. The deformation effect of the RBF hull is shown in Fig. 1, the red points are the RBF control points.



(a) The initial hull of Wigley



(b) After deformation of Wigley using RBF

Fig. 1 Comparison of deformation effect using RBF

Shifting Method is an easy and practicable hull form deformation method. The modification function is applied to modify the section area curves. The modification function is shown as equation (15):

$$g = \begin{cases} \alpha_1 \left[0.5(1-\cos 2\pi \dfrac{x-\alpha_2}{\alpha_2 - x_1}) \right]^{0.5}, & x_1 \le x \le \alpha_2 \\ -\alpha_1 \left[0.5(1-\cos 2\pi \dfrac{x-\alpha_2}{\alpha_2 - x_2}) \right]^{0.5}, & \alpha_2 \le x \le x_2 \\ 0, & elsewhere \end{cases} \tag{15}$$

Where x1, x2 is the shifting range of hull form deformation along the direction of the hull. α1 represents the amplitude of the modified function, and α2 is the coordinate of fixed points in the deformation region. Based on the modification function, we can get the new coordinates when the initial coordinates are given along the direction of the hull. The advantages of the Shifting Method are fewer variables, higher modification efficiency.

Hydrodynamic Performance Evaluation

For hull form optimization, it is important to get the hull hydrodynamic data quickly so that we can get enough hydrodynamic data about samples, which is the basis of constructing BP neural network surrogate. The Neumann-Michell potential theory is used in this paper and Liu, Wang, and Wan (2018) have carried out some studies using the NMShip-SJTU. The NMShip-SJTU solver is self-developed based on the Neumann-Mechell theory using the C++ language. We can get the wave-making resistance of the hull, wave height along with the ship, and the wave elevation of the free surface within about ten minutes using the NMShip-SJTU. Thus we apply the solver to acquire the wave-making resistance coefficient and combined the ITTC formula, shown as equation (16). we finally obtain the total resistance.

$$C_f = \frac{0.075}{(\lg \mathrm{Re} - 2)^2} \tag{16}$$

Surrogate Model Construction——BP Neural Network

BP (Back Propagation) neural network, also known as the error Back Propagation neural network, is widely used in the Marine and ocean engineering fields due to its strong nonlinear mapping ability and generalization ability. Mathematical theory shows that a simple three-layer neural network can fit any functions with high precision. The construction of the BP neural network is divided into the input layer, hidden layer, and output layer, as shown in Fig. 2. By learning the sample data, the implicit or explicit relationship between the input layer and the output layer can be obtained. In this paper, a three-layer fully connected network is adopted, and the activation function is the sigmoid function. The trained neural network function can be expressed by the following formula：

$$O_i = \sum_{j=1}^{J} W_{ij} a(\sum_{k=1}^{K} W_{jk} sigmod(\sum_{n=1}^{N} W_{kn}\xi_n + b_{1k}) + b_{2j}) + b_{3i} \tag{15}$$

Where O_i is the output variable; ξ_n is the input variable; W_{kn}, W_{jk}, W_{ij} are the weights of neurons in each layer; b_{1k}, b_{2j}, b_{3i} are the threshold value of each layer of neurons; i, j, k are the number of neurons in the input layer, the hidden layer, and the output layer in the neural network. Error backpropagation refers to the error between the actual output value and the expected output value. In the training process, the weights and biases of each layer of the network will be adjusted layer by layer according to the change of errors, so that the network output will finally get close to the expected output as far as possible.

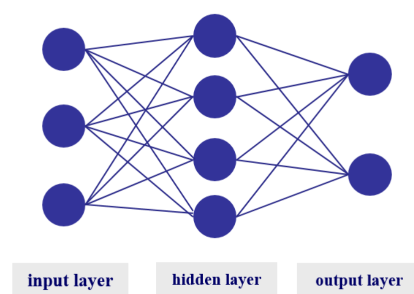


Fig. 2 Neural network diagram

In this paper, a three-layer neural network is adopted, with 7 neurons in the input layer, 10 neurons in the hidden layer, and 1 neuron in the output layer. Levenberg-Marquardt Backpropagation training algorithm is adopted. The hidden layer activation function is Sigmoid function and the output layer activation function is a linear function. 140 samples hull are used to train the neural network.

Optimization Algorithm

After constructing the BP neural network arrogate model, the genetic algorithm (Deb, Agrawal, Pratap, and Meyarivan) is chosen as the optimization algorithm solving the single-objective optimization problem. because the neural network is an implicit function, the rand search algorithm is used to find the best parameter based on the neural network. The iterations are 250 and the initial population is 60, the crossover fraction of genes swapped between individuals is set as 0.8, and the mutation rate is 0.2.

HULL FORM OPTIMIZATION

Initial Hull Validation

In this section, 4m Wigley ship is adopted as the initial ship when Fr=0.3, shown as Fig. 4 and Table 1. The NMShip-SJTU program based on the Neumann-Michell theory was used to calculate the wave-making resistance coefficient, and the 1957 ITTC formula was used to calculate the frictional resistance coefficient, to obtain the total hull resistance and compare with the standard experiment data to verify the accuracy of the solver.

Table 1 Main dimensions of Wigley

Ship	Length/m	Width/m	Height/m
Wigley	4	0.4	0.25

Fig. 3The parent model of Wigley

For NMShip-SJTU, the grid of the hull and free surface is needed to calculate the wave-making coefficient. The hull mesh and the free surface mesh is shown as Fig. 4

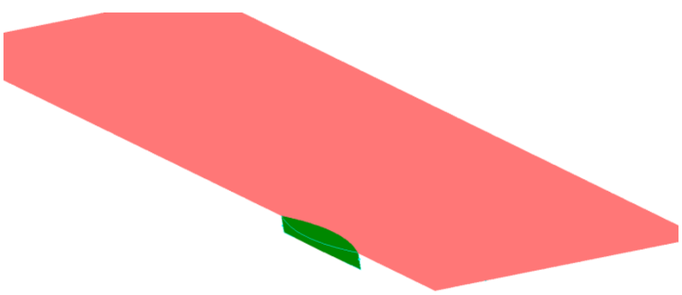


Fig. 4 Hull mesh and free surface mesh

The final calculation and verification results are shown in Table 2.

Table 2 Compared the calculation results with the experiment

Fr	U (m/s)	Cw (10^{-3})	Cf (10^{-3})	Ct(10^{-3})	EFD (10^{-3})	Error
0.3	1.8793	1.6609	3.2297	4.8901	5.033	2.83 %

Through the validation of the initial ship, it can be seen that the precision of the NMShip-SJTU solver meets the engineering application requirements. Then, the hull deformation module of OPTShip-SJTU is used to deform the initial ship with 7 deformation variables, and the RBF deformation method is used to move the three control points of the bow of the Wigley with 3 variables. The latter part of the hull is deformed by shifting method, and deformation variables were 4. Finally, we can get 140 sample ships based on the deformation module, the variables are shown in Table 3. P1-x control the distance of the control points in the bow along the x-axis, P1-y control the distance of the control points in the bow along the y-axis, P1-z control the distance of the control points in the bow along the y-axis. The parameters α1, α2 of Shifting method control the first half of hull and the α3,α4 control the second half of hull.

NMShip-SJTU was used for hydrodynamic assessment and combined with ITTC formula to calculate the total resistance corresponding to 140 sample ships when Fr=0.3.

Table 3 Hull deformation parameter

Number	Deformation methods	Deformation variables	Range
1	RBF	P1-x	[0.515,0.545]
2		P1-z	[-0.049,-0.0344]
3		P2-y	[0.005,0.021]
4	Shifting	α_1	[-0.02,0.02]
5		α_2	[0.2,0.3]
6		α_3	[-0.02,0.02]
7		α_4	[-0.3,-0.2]

Surrogate Model —BP Neural Network

Through the establishment of a three-layer BP neural network, 140 sample data were learned to obtain the BP neural network surrogate model after training. The goodness of fitting of the approximate model is shown in Fig. 5 and the fitting accuracy meets our requirements.

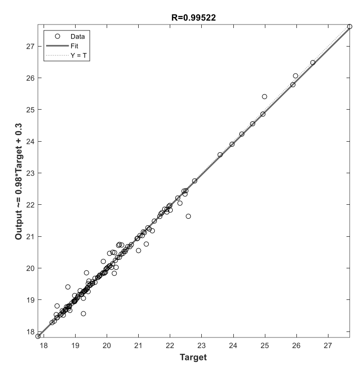


Fig. 5 Neural network fitting quality

The predicted value obtained by the neural network surrogate model was compared with the expected value of the sample data. Fig. 6 shows that the accuracy of the neural network surrogate model obtained by training meets our requirements. The maximum error is 2.24% and the average error is 0.0432%.

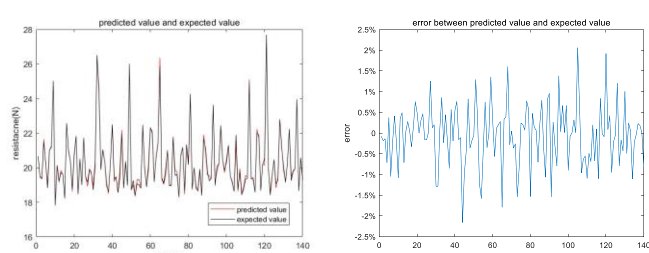


Fig. 6 Comparison of neural network predicted value with expected value and error

Optimization results and analysis

After the neural network surrogate model is established, the genetic algorithm is used for optimization. After 250 iterations, the optimal resistance value is 16.92324 N, shown as Fig. 7.

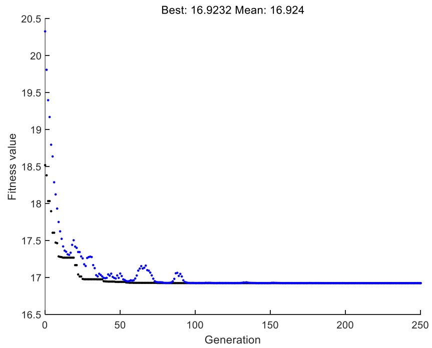


Fig. 7 Genetic algorithm fitness

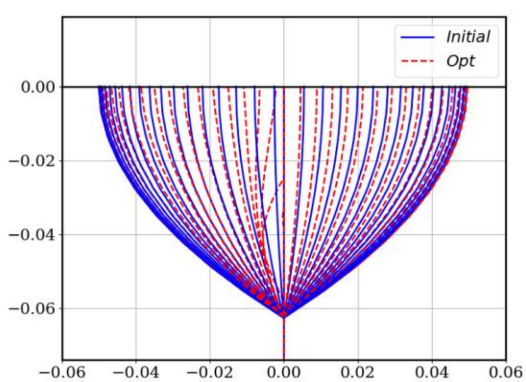
The corresponding optimal variables are shown in Table 4：

Table 4 The optimal parameters

Parameters	P1-x	P1-z	P2-y	
value	0.545	-0.03447	0.005489	
Parameters	α_1	α_2	α_3	α_4
value	0.02	0.2132	0.02	-0.20

To verify the optimization results, the hull is deformed according to the optimal hull deformation variables. The initial ship and the final optimized ship are shown in Fig. 8. Then, NMShip-SJTU is applied to calculate the wave-making coefficient of optimal hull form, and comparison with the initial hull, shown as Table 5

(a) the comparison of ship surface between the initial hull and optimized hull



(b) the comparison of ship curves between the initial hull and optimized hull

Fig. 8 The optimal Wigley hull

Table 5 The comparison between the initial hull and optimized hull

	Fr	U(m/s)	R(w)/N	R(f)/N	R(t)/N
Initial Hull	0.3	1.8793	7.013016	13.546817	20.5598
Optimized Hull			3.918431	13.728681	17.6471

The comparison shows that the total resistance of the optimized hull type decreases by 14.167%, among which the wave-making resistance decreases by 44.126%. The error between the optimal value obtained by the genetic algorithm and the verification value is 4.27%, which indicates that the accuracy of the neural network approximate model can meet the practical requirements. By observing the free surface, shown as Fig. 9, the wave-making around the hull and the wake field decrease because of existing of the bulbous bow.

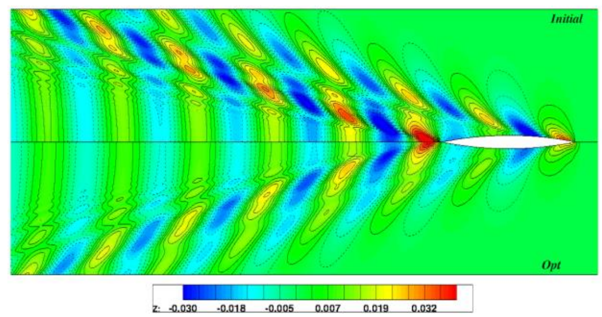


Fig. 9 Free surface comparison between the initial hull and optimal hull

Sensitivity Analysis

Based on the neural network model, a sensitivity analysis of the deform parameters is conducted. Firstly, we change one of the parameters and keep the other parameters the same. The interval of each parameter is divided into 5 parts equally. If the input is important to the solution, the result will change drastically. The result is shown in Fig. 11.

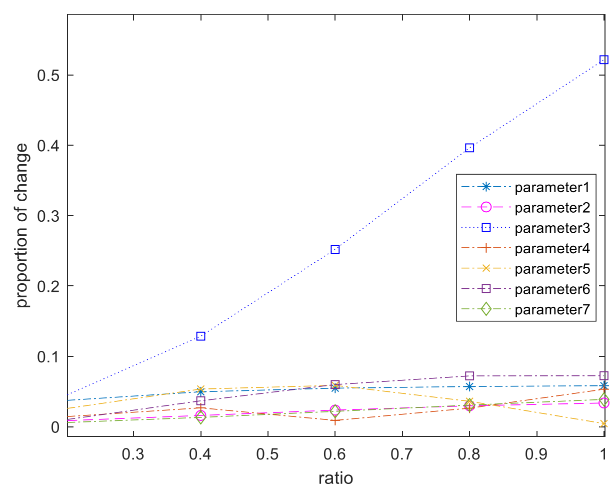


Fig. 11 Sensitivity analysis of 7 parameters

From Fig. 11, the sensitivity analysis shows that the parameter 3 has a great impact on the result, over 50 percent. From before, the parameter 3 controls the bow bulbous of Wigley, thus, we can realize that the form of bow bulbous is essential for the decreasing of total resistance.

CONCLUSION

In this paper, the deformation module of hull form optimization software OPTShip - SJTU is used to deform the Wigley hull, and the potential flow solver NMShip - SJTU is used to get wave-making resistance and which combined with ITTC formula to get total resistance. Based on the establishment of the neural network surrogate model, we use the single-objective genetic algorithm to get the best total resistance performance Wigley hull with a bulbous bow. A 14.167% drop in total resistance, and the wave-making resistance drop by 44.126%, which presents the OPTShip-SJTU have well performance in hull form optimization, and we can realize the bulbous bow is very important to reduce the wave-making resistance. At the same time, we can realize that for large hull deformation RBF deformation method have well performance. For the hull without bow bulbous, the RBF method in deformation can generate bulbous bow, and meanwhile, the hull can be fully smooth without affecting subsequent mesh generation, which has great application potential.

ACKNOWLEDGEMENTS

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