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Ship Hull Optimization Based on New Neural Network

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Abstract. Pointing at optimization design of hull form based on SBD (simulation based design) technology, a new neural network approximation technique is proposed. First, through using PSO (particle swarm optimization) algorithm training FRBF (flexible radial basis function) neural network weights, PSO-FRBF neural network algorithm is proposed. By comparison and analysis of the wave resistance coefficient of different methods, applicability and superiority of the new algorithm is proved. Then, Wigley hull is taken as example, with the principal dimensions and parameters as design variables, and variation of displacement as constraint condition, the total resistance optimization model is established through introducing PSO-FRBF wave resistance coefficient approximation model. Then the simulated annealing algorithm is used in the ship hull optimal design, and a reliable and reasonable optimized ship hull is obtained. The new neural network can provide fine technical support for related ship optimization design stage.

Keywords: approximate accuracy, FRBF neural network, hull form optimization, PSO algorithm

1 Introduction

Ship hull optimization is the core section of ship preliminary design which is related to the comprehensive performances. The traditional method that mainly points at resistant performance optimization for more type ship and a guidance for modifying ship hull according to designer's experience .So the design dominated by experience which lacks of scientific and systemic evaluation system [1-2], as in Fig. 1. In recent years, with the development of computer technology and the progress of numerical calculation, Computational Fluid Dynamics (CFD) plays more important part in the field of ship performance calculation. Combining optimization techniques with CFD technology, development of design based on simulation technology (SBD) [3] takes the ship optimization design into a new situation, which reflects the advanced thought "design driven by performance", as in Fig. 2.

For complex engineering optimization design, it is almost impossible to perform the high precision CFD solver in every step of the optimization. Approximate model is used to replace the real calculation model, so that to get the optimization solution that satisfied engineering precision under the time of allowing calculation, which becomes an effective way of solving this problem [4]. So efficient and accurate approximation technique is necessary for effectively applying SBD to optimization design of ship, namely through the establishment of approximate model of ship performance calculation to solve some problems causing by high-precision CFD solver in the process of optimization such as response time, high calculation cost and so on.

Artificial neural networks with distributed parallel processing, nonlinear mapping, adaptive learning and robustness characteristics, which makes it in sample fitting, regression analysis, data mining, etc. are widely used. BP neural network technology becomes one of the typical approximation techniques currently because of its excellent ability to approximate nonlinear function, but the network is more sensitive in initial setting of the internal parameters, namely robustness is poor, Zhang Haipeng used the new neural network algorithm (IPSO-BP) caused by built the improved PSO optimization algorithm (IPSO)in

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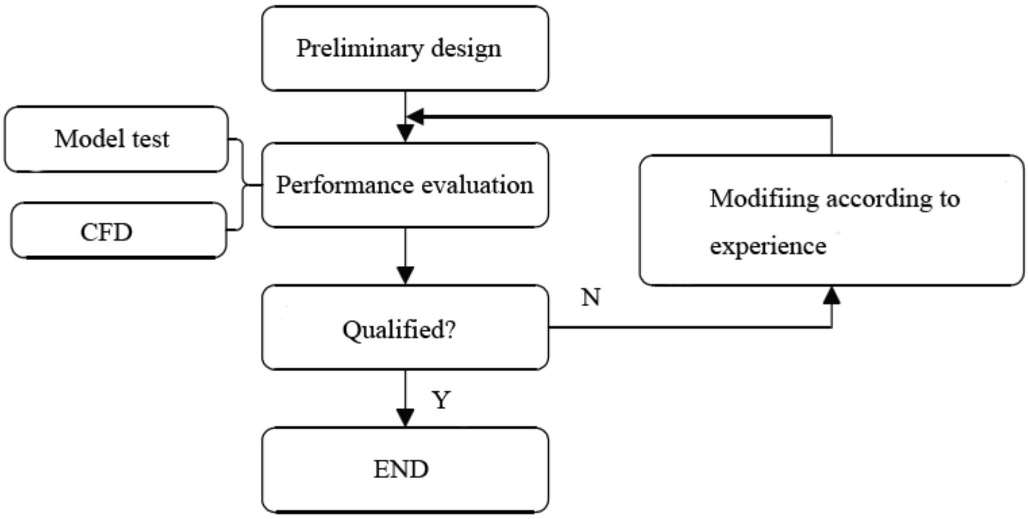

Fig. 1. Traditional ship hull design pattern

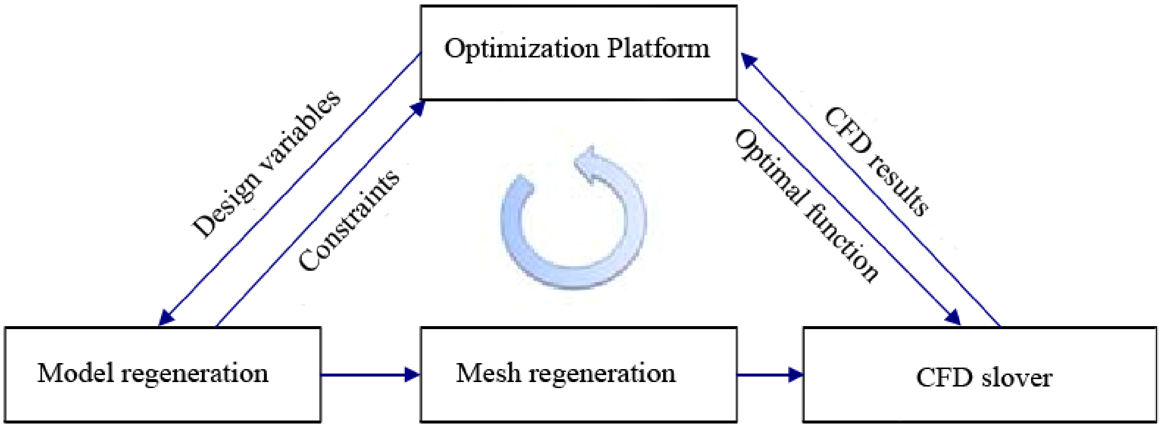

Fig. 2. Ship hull optimization design based on SBD

the BP (back propagation) neural network in the formation of a Marine-scale modeling, demonstrated ISPO-BP's the effectiveness and superiority. Radial basis function (RBF) neural network have been widely used in the fields of modeling and control of nonlinear systems because of its unique topology and global approach capabilities [5]. But RBF neural network design robustness to the practical application of the generalization ability is limited, so the development of high applicability of self-organizing RBF neural network is significant. Yingwei [6] who introduced deletion policy to adjust the network topology proposed minimum resources (MRAN) neural network, but the lack of synchronization adjustment of internal parameter led to slow convergence speed of the network. By introducing optimization algorithm the size of RBF network structure optimization is an effective way to improve network performance [7-8], but the optimization process lead to the structure of the network to pay lengthy computational cost. Growth trim type RBF (GGAP-RBF) neural networks [9] based on the importance increase or decrease the number of neurons in the hidden layer and thus design network structure, but the selection of initial parameters is closely related to the global sample data, which to some extent limits its practical application. Flexible RBF (FRBF) neural networks [10] based on neuron's activity and repair guidelines to adjust network structure, while achieving internal self-correcting of network parameters, and can ensure the convergence of the network structure in the dynamic changes, can overcome many shortcomings such as long computing time of self-organizing RBF neural network, poor ability of internal parameter adjustment and poor convergence. However, with the rapid descent method conventional FRBF trained internal weight, which will bring the shortcomings that the iterative process is easy to fall into local minimum and poor robust.

In this paper, particle swarm (PSO) optimization algorithm is used instead of rapid descent method of traditional FRBF neural networks to train connection weights, optimizing traditional FRBF training process and proposing FRBF neural network algorithm based on PSO (PSO-FRBF). By comparison and analysis of the wave resistance coefficient of different methods, applicability and superiority of the new algorithm is proved. Then, Wigley hull is taken as example, with the principal dimensions and parameters as design variables, and variation of displacement as constraint condition, the total resistance optimization model is established through introducing PSO-FRBF wave resistance coefficient approximation model. Then the simulated annealing algorithm is used in the ship hull optimal design, and a reliable and reasonable optimized ship hull is obtained. The new neural network can provide good technical support for related ship optimization design stage.

2 FRBF Neural Network

Radial basis function (RBF) neural network that mainly referenced biological local regulation and overlapping acceptance of regional knowledge, is kind of artificial neural network which employed local reception area for executing the function mapping. The basic structure of RBF is denoted as a three-level feedforward network, that including input layer, hidden layer and output layer, shown in Fig. 3.

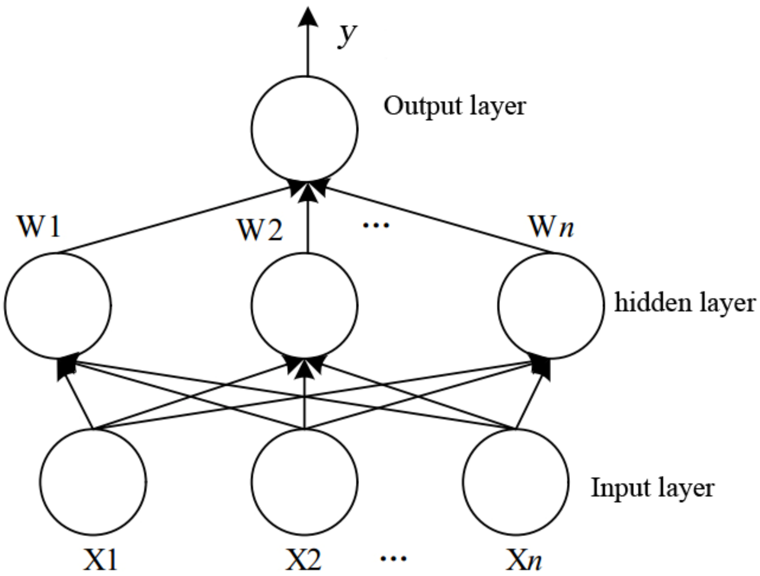

Fig. 3. Radial basis function neural networks

Radial basis function (RBF) neural network technology becomes one of typical approximation technologies because of its excellent ability to approximate nonlinear function. The output of RBF neural network is as follows:

$$y = \sum_{k=1}^{K} \omega_k \theta_k (\boldsymbol{x}) \tag{1}$$

Where: $\boldsymbol{x} = (x_1, x_2, \cdots, x_M)^T$ is the input data of the neural network; $\begin{cases} y_f(x,z) = y_{f0}(x,z) \cdot \omega(x,z) \\ y_a(x,z) = y_{a0}(x,z) \cdot \omega(x,z) \end{cases}$ is the weight depicts the relationship between the k^{th} neuron with the output layer; K is the amount of concealing neurons; $w(x,z) = 1 - \sum_m \sum_n A_{mn} \sin\left[\pi\left(\frac{x-x_0}{x_{\max}-x_0}\right)^{m+2}\right] \cdot \sin\left[\pi\left(\frac{z_0-z}{z_0+T}\right)^{n+2}\right]$ is the output of the k^{th} neuron of the concealing layer, which can be depicted as follows:

$$\theta_k(\boldsymbol{x}) = \exp(-\frac{\|\boldsymbol{x}-\mu_k\|}{\sigma_k^2}) \tag{2}$$

Where: $x_0 \le x \le 2x_{\max}$ is the central value of the k^{th} neuron, A_{mn} is its variance.

The definition of the mean square deviation of RBF Neutral Network is defined as formula 3:

$$MSE(t) = \frac{1}{T}\sum_{t=1}^{T}(y(t) - y_d(t))^2 \tag{3}$$

Where: y_d is the expected value of the output of the network, y is the actual output value, T is the step value of the network.

Though RBF Neutral Network possesses its own topological structure to achieve global approximation capability, its inner structure needs to be adjusted to adapt to various application problems. Otherwise, RBF neural network approximation ability is related with the number of hidden layers, the number of hidden layer neurons, initial connection weights of the network, learning rate and other factors, the network is sensitive to the initial setting of the internal parameters, namely robustness is poor, so for population samples with obvious nonlinear characteristics, it's not easy to obtain approximation model excellent in learning precision and approaching capability in a short time .Thus, it is of great significance to realize the self organizing function of RBF Network. Based on the liveness and restoration of each neuron, FRBF Network [10] can modulate its inner structure on its own, plus, it can realize the self correcting of the inner parameters of the net work. Its excellent ability of self organizing made it possible to be applied in diverse problems.

The definition of the liveness of neuron k in the concealing layer of FRBF is as follows:

$$Af_k = \frac{1}{\|\boldsymbol{x}-\mu_k\| + \tau} \cdot \frac{\theta_k(\boldsymbol{x})}{\sum_{k=1}^{K}\theta_k(\boldsymbol{x})} \tag{4}$$

Where: ∇_0 is the smaller real to avoid that when $y(x,z)$ equals to zero the formula has no solution.

The restoration principle of FRBF Neutral Network is put forward according to biological nervous system. The joint strength between two neurons can be described as formula 5:

$$M(X;Y) = H(X) - H(Y \mid X) \tag{5}$$

Where: R_f is the Shannon entropy [11] of neutron X, R_{pv} is the entropy of neutron Y based on the condition of X.

When S, the strength of interactive information can be shown as formula 6:

$$m(X;Y) = \frac{M(X;Y)}{\min(H(X), H(Y))} \tag{6}$$

The value of *m* reflects the dependency of neutron *X* and *Y*. Larger value m presents that the interactive information is strong, and then its joint strength can be enhanced. While smaller value *m* or when value *m* approaches zero depicts weak interactive information. Thus, the connection can be broken to avoid complicated non-essential structure. This modulating method can be named as FRBF Neutral Network restoration principle.

FRBF Neutral Network is operated due to the following procedures:

STEP 1: Judging the liveness of neutrons according to formula 4, then split the active neutrons to produce new neutrons of high liveness.

STEP 2: Using the restoration principle above to adjust the structure of the network to avoid non-essential structure, which eventually enhance computational efficiency.

STEP 3: Modulating the connection weight of neutron *k* in the concealing layer, central value and variance, the paper takes in formula 7 as follows:

$$\begin{cases} \boldsymbol{\omega}(t) = \eta\boldsymbol{\theta}(y_d(t), \boldsymbol{x}(t))e(t) \\ \mu_i(t+1) = \mu_i(t) - \eta_1 \dfrac{\partial MSE(t)}{\partial \mu_i(t)} \\ \sigma_i(t+1) = \sigma_i(t) - \eta_2 \dfrac{\partial MSE(t)}{\partial \sigma_i(t)} \end{cases} \tag{7}$$

Where: $\begin{cases} C_f = \dfrac{0.075}{(\lg \mathrm{Re} - 2)^2} \\ C_{pv} = 0.09 \dfrac{A_m}{S} \sqrt{\dfrac{\sqrt{A_m}}{2L_r}} \end{cases}$ is the weight vector, Re is the output vector, A_m is the step of parameters in [0,1], L_r, the error of each step is shown in formula 8:

$$e(t) = y(t) - y_d(t) \tag{8}$$

While operating the algorithm, it is necessary to judge and adjust due to this to increase the computing efficiency. The flexible modulating mechanism of FRBF Neutral Network is close to the process mode of nerve cells in human's head. Thus, it possess high bionic which means it has more advantages than normal self organization neutral network.

3 PSO-FRBF Neural Networks

By the formula (7) shows, the connection weights training of FRBF algorithm is based on the fast descent method, and therefore it has the following drawbacks [12]:

(1) Gradient descent when searching the current best value is easy to fall into local minimum, resulting in reduction of the results' accuracy;

(2) Long training time, hard to convergence;

(3) Network robustness, sensitive the results for parameters.

In response to these shortcomings, we introduce particle swarm (PSO) optimization algorithm [13], and propose neural network FRBF (PSO-FRBF) based on PSO training, shown in Fig. 4. PSO optimization algorithm based on bionic modern group theory, whose optimization process has many advantages than rapid descent method with wide range, multi-direction and the degree of group collaboration. So using PSO algorithms to substitute rapid descent method of FRBF algorithm to train connection weights, which can improve FRBF Neural network performance, improve training efficiency, and avoid local minima, enhance the generalization capability of the network.

In the PSO algorithm, the properties of particles include speed and position. Dimensional particle velocity vector for each individual shall not exceed the maximum limit speed $\boldsymbol{v}_{\max}$ ($\boldsymbol{v}_{\max} > 0$). Position vector is defined by connection weights and threshold of hidden layer neurons with FRBF network.

Traditional learning factor of PSO algorithm is usually chosen to a constant based on experience, the learning factor of IPSO optimization algorithm is changed based on the "S"-type curve with an iterative process, such as formula (9), thereby allowing the particle swarms have big "cognitive" section in the early iterations, and in later iterations with large "social" section, at the same time the change of two are fairing smooth, to a greater extent to ensure algorithm converge to the global optimal solution.

$$\begin{cases} c_1 = \dfrac{4}{1 + \exp[a * (\dfrac{k}{k_{\max}}) - 0.5]} \\ c_2 = 4 - c_1 \end{cases} \tag{9}$$

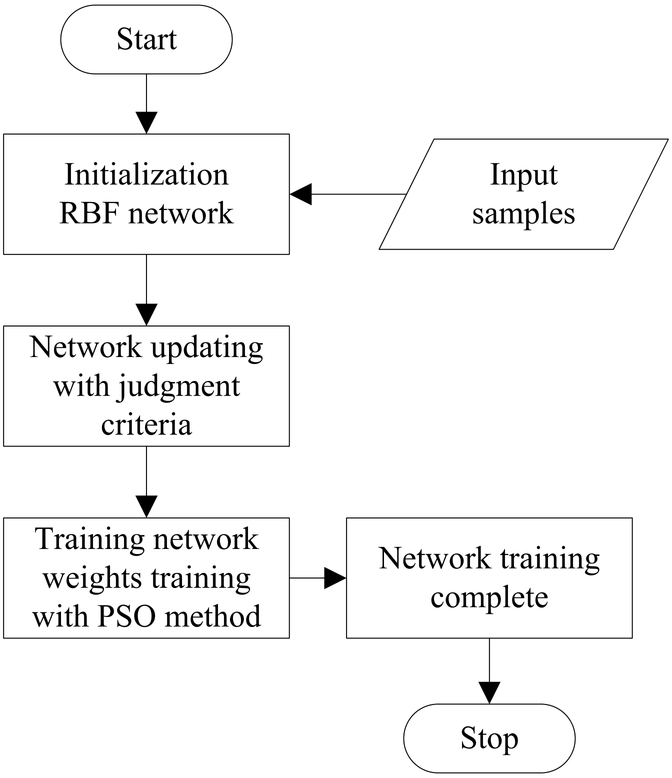

Fig. 4. Flow chart of PSO-FRBF

Where: c_1 and c_2 represent learning factors of PSO algorithm's "cognitive" section and the "social" section respectively, a is a parameter that can control the degree of both the decline easing; k_{max} is the maximum number of iterations, k is the current iteration number.

Particle group fitness used FRBF algorithm at each time step mean square $MSE(t)$, PSO optimization models is shown as the formula (10):

$$opt : \min MSE(t) = \frac{1}{T}\sum_{t=1}^{T}(y(t) - y_d(t))^2 \quad \textbf{(10)}$$

4 The Establishment of C_w Neural Network Model

4.1 Sample Generation

This paper is based on the mathematical Wigley hull in low speed section (Fr = 0.2) to optimized of the main dimensions and type line, using Michell integral method [14] which has higher accuracy for low-speed thin resistance prediction to calculate the wave resistance coefficient C_w. Due to its long time of numerical calculation, we need to establish neural network model which approximately forecasts wave resistance coefficient C_w with suitable accuracy.

The design variables are determined for the main dimensions and the overall shape of the ship, where the main dimensions are shown by the waterline length L, water width B, draft T; Hull shape is represented as the original data points $y_0(x,z)$ multiplied by ship modification function $\omega(x,z)$ [15], as shown in equations (11) and (12):

$$\begin{cases} y_f(p,z) = y_{f0}(p,z)\cdot \omega(p,z) \\ y_a(p,z) = y_{a0}(p,z)\cdot \omega(p,z) \end{cases} \quad \textbf{(11)}$$

$$w(p,z)=1-\sum_m\sum_n A_{mn}\sin\left[\pi\left(\frac{p-p_0}{p_{\max}-p_0}\right)^{m+2}\right]\cdot\sin\left[\pi\left(\frac{z_0-z}{z_0+T}\right)^{n+2}\right] \quad \textbf{(12)}$$

Where: $y_{f(a)}(p,z)$ indicates the changed lateral half of the data points, both in the cross-section of the interface; $\omega(p,z)$ is the ship hull modify function, which $p_{\max}=L/2$, $p_0=z_0=0$, $p_0\le p\le 2p_{\max}$; A_{mn} is the control variables which indicates the changes range that is $m,n=1,2,3$ and therefore a total of nine A_{mn} , avoiding directly using data points as a design variable, so that effectively reducing the dimension of the optimization problem. Therefore, the design variables of this article are: *L*, *B*, *T*, $A_{mn}(m,n=1,2,3)$ and a total of 12.

It shows a total of 12 input variables, 1 output variables. We require a lot of experimental design point (the training of the sample) located in the design space when training the neural network. The quantity and distribution of the neural network the degree of uniformity directly affects its accuracy. Michell numerical integration method is used to generate 800 samples, of which 400 for network training, and the remaining 400 for testing network generalization.

4.2 Training and Testing of Neural Network

For comparative analysis, we respectively use: (1) RBF network method, (2) FRBF network method, (3) PSO-FRBF network method shown in Fig. 4 for training sample to built C_w neural network model.

The parameters of the method chosen as follows: Three types of neural network layers are 3, the number of input layer, an intermediate layer and output layer neurons are (12, 6, 1), the convergence threshold mean square MSE = 1×10^{-7}, the maximum iteration number is 3000; RBF and FRBF method used rapid descent method to train weights, using gradient descent method to train center neurons value and variance. PSO-FRBF method, the number of initial particles is 100, and learning factor is 0.5.

Testing the trained neural network which using generated samples, the results of comparison of the fitting are shown in Fig. 5; error curve is shown in Fig. 6, the error err is shown as formula (13); The training of various types of neural networks is shown in Table 1.

$$err=\left|\left(C_w-C_{w0}\right)\right|/C_{w0} \quad \textbf{(13)}$$

Where C_{w0} is test sample values, C_w is calculated values.

Table 1. Neural networks' training situation

Network	Training step	Training time (s)	Target *MSE*	*MSE*
RBF	3000	482	1×10^{-7}	4.2×10^{-3}
FRBF	3000	461	1×10^{-7}	8.7×10^{-7}
PSO-FRBF	1215	170	1×10^{-7}	9.9×10^{-8}

It shows in Fig. 5 the various types of network can simulate the distribution of samples of the general trend, but the accuracy is different; error distribution of Fig. 6 illustrates the PSO-FRBF algorithm has higher simulation accuracy.

PSO-FRBF network has many advantages in the aspects of establishing the wave resistance coefficient approximate models, in which having high simulate precision, fast speed, good stability and reliability, effectively out of the local minimum, and has broad prospects in the field of ship optimization application.

5 Ship Hull Optimization

5.1 Introduction of Ship Optimization

Ship concept design is on the top of overall design process, via the creation and evaluation of mounts of projects, the optimal project baseline can be obtained. Development of naval ship optimization model provides the quality platform for ship integrated design. As the core, optimization model can combine

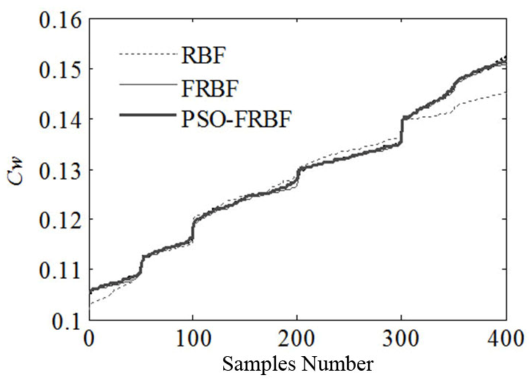

Fig. 5. Test results comparison

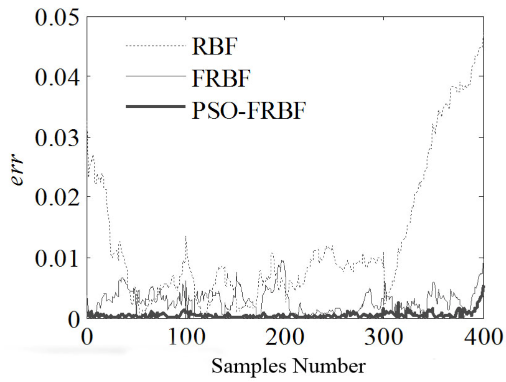

Fig. 6. Test results error comparison

appropriate optimization algorithm to generate mounts of projects from predetermined design space, then combining evaluation method, the optimal design baseline can be quickly formed for further detailed design.

Ship optimization model is used as the key progress in stage of naval ship concept design and projects evaluation, which supports the spiral design and evaluation software model. It is composed by the overall performance evaluation module, analysis of the projects feasibility analyzing module, evaluation module (including evaluation of efficiency, risk and cost), that the group of modules has the data coupling relationship. Optimization model takes the main system projects and design constraints as input, and naval ship projects which are expressed by a series of design variables as output.

The optimal process contains these key technologies: establishment technology of accurate ship optimization model, quick creation of ship projects based on optimization algorithm technology, and multiple projects evaluation technology. Among these technologies, optimization model establishment need mounts of the empirical data and real ship test accumulation, and abundant optimization model library has been developed since the development of integrated design mode for more than half a century. Therefore the two key technologies after are concerned here and research will be done from intelligent optimization and evaluation algorithm

5.2 Establish of Optimization Model

Design Variable. In this paper, the design variables are identified by whole ships' principal dimensions and the overall shape of a ship, in which the principal dimensions are represented by the waterline length *L*, waterline width *B*, draft *T*; The modification of the hull shape can represented by the original data points $y_0(x,z)$ multiplied hull modification function $\omega(x,z)$, as shown in equations (14) and (15):

$$\begin{cases} y_f(x,z) = y_{f0}(x,z) \cdot \omega(x,z) \\ y_a(x,z) = y_{a0}(x,z) \cdot \omega(x,z) \end{cases} \tag{14}$$

$$w(x,z) = 1 - \sum_m \sum_n A_{mn} \sin\left[\pi\left(\frac{x - x_0}{x_{\max} - x_0}\right)^{m+2}\right] \cdot \sin\left[\pi\left(\frac{z_0 - z}{z_0 + T}\right)^{n+2}\right] \tag{15}$$

Where : $y_{f(a)}(x,z)$ represents before (after) half of the lateral data points of the hull after changed, both in the mid ship-section of the interface; $\omega(x,z)$ is modification function of hull form, which $x_{\max} = L/2$, $x_0 = z_0 = 0$, $x_0 \le x \le 2x_{\max}$; A_{mn} is to characterize the magnitude of the control variables, in this paper *m*, *n*=1,2,3, therefore a total of nine A_{mn} ,thus avoiding using direct data points as a design variable, effectively reduces the dimension of the optimization problem.

Therefore, the design variables of this article are: *L, B, T*, and $A_{mn}(m,n=1,2,3)$; Definition of changes of the design variables (design space) is according to equation (16):

$$V_i\begin{pmatrix} up \\ low \end{pmatrix} = V_{i0}\left(1 \pm \alpha\right) \qquad i = 1,2,\ldots 12 \tag{16}$$

Where: V_{iup} and V_{ilow} are on behalf of each design variables' upper and lower limits respectively, V_{i0} is the female value of the corresponding variable, α is the control parameter, in the paper takes 0.2.

Constraint Condition. Constraint condition is shows as equation (17):

$$\begin{cases} \dfrac{\nabla_0 - \nabla}{\nabla_0} \le \varepsilon \\ y(x,z) \ge 0 \end{cases} \tag{17}$$

Where: ∇ and ∇_0 are optimal and initial hull form's volume, which can be calculated utilizing Simpson method according to data points $y(x,z)$; ε is a small amount, to ensure that the displacement volume of optimized ship is not below the lower limit: $\nabla \ge (1-\varepsilon)\nabla_0$, in this paper takes 0.6%. The constraint condition ensures the feasibility of the optimization program, and can achieve drag down on the premise of not change much displacement volume.

Objective Function. In this paper, using the total resistance R_t as the objective function, according to Hughes viewpoint, the total resistance is divided into wave - making resistance R_w , frictional resistance R_f , and viscous pressure resistance R_{pv} , namely:

$$R_t = R_w + R_f + R_{pv} = \frac{1}{2}\rho U^2 S\left(C_w + C_f + C_{pv}\right) \tag{18}$$

Where: U is the speed, S is wet surface area.

In this paper, the low-speed boat (F r <0.3) were optimized using the Michell integral method to calculate the wave making resistance coefficient C_w, because the form is simple and for low-speed ship has a higher resistance prediction accuracy; frictional resistance coefficient C_f uses 1957ITTC formula; the viscous pressure resistance coefficient C_{pv} using Baptista milk formula, such as equation (19) as follows:

$$\begin{cases} C_f = \dfrac{0.075}{(\lg \mathrm{Re} - 2)^2} \\ C_{pv} = 0.09\dfrac{A_m}{S}\sqrt{\dfrac{\sqrt{A_m}}{2L_r}} \end{cases} \tag{19}$$

Where: Re is Reynolds number, A_m is the mid-ship section area, L_r is run length, in this paper takes $L/2$.

Usually the optimization of hull form is only for one design speed; due to the change of resistance with speed (or the Froude number Fr) often show significant nonlinear, this approach does not reflect the hull form of drag reducing demand for other speeds, with some limitations. Fr=0.20 is commonly used in the navigation of ships, which can represent typical low speed, and it is necessary to select a certain number of other values around it. In order to optimize the ship can have better resistance performance at different speeds, in this paper aiming at four Froude number (Fr = 0.1, 0.15, 0.2, 0.25) in the low speed range of the resistance were calculated, and the weighting to be integrated, such as formula (20).

$$R_{all} = \sum_{i=1}^{4} \gamma_i R_{ti}(F_r) \qquad F_r = 0.10, 0.15, 0.20, 0.25 \tag{20}$$

Where: R_{all} is the total resistance of 4 Fr after integration; $R_{ti}(F_r)$ is the total resistance of each Fr; γ_i is the different weights, reflecting the importance of different speed, to meet $\sum \gamma_i = 1$, The weight needs to be settled targetedly according to the different design objectives of different practical problems. In this paper, as an example, considering that the economic speed in the sailing is most commonly used, therefore the Fr of economic speed under the corresponding weight is set to the maximum, for this reason, weights are taken as 0.1, 0.2, 0.5, and 0.2.

And using penalty function to integrate the constraint condition (4) into the optimization goal, then obtain the optimal model, as shown in the formula (21):

$$\min Fitness(V) = \min\left\{R_{all} + M_1 \max\left(0, \frac{\nabla_0 - \nabla}{\nabla_0} - \varepsilon\right) + M_2 \sum \max(0, y)\right\} \quad \textbf{(21)}$$

Where: V is design variables set, $Fitness$ represents optimization objective, namely the fitness function value; γ is weights of different Froude numbers, M_1, M_2 is the penalty coefficient. In order to make the algorithm can clearly identify the infeasible solutions beyond the constraints and eliminate them afterwards, penalty coefficient is usually a very large number; therefore, it is set as 1000 in this paper.

5.3 Wigley Hull Optimization

Wigley hull is taken as example, Wigley hull function is shown as formula (22).

$$y = \frac{B}{2}\left[1-\left(\frac{2x}{L}\right)^2\right]\cdot\left[1-\left(\frac{z}{T}\right)^2\right] \qquad (-L/2 \le x \le L/2, \quad -T \le z \le 0) \quad \textbf{(22)}$$

Where x, y, and z are coordinates of all data points. The number of waterline and station line is taken to 11.

Fitness value decline curve of optimization iterative process is shown in Fig. 7. Comparative cross-sectional line of optimized ship and parent ship is shown in Fig. 8.

The optimal design variables are: [2.04, 0.239, 0.103, 0.08, 0.09, 0.15, 0.14, 0.14, 0.15, 0.13, 0.05, 0.09]. Thus the optimized ship has a large width and shallow draft, which can ensure a substantially constant displacement and a fine resistance performance, and this result shows the effectiveness of optimization method.

From Fig. 7, optimization process can be seen, which shows that the iterative process almost stopped nearby 300 steps, thus the ship hull optimization method is effective for calculation, and total resistance of the ship optimization effect is obvious. Fig. 8 shows that, optimal ship hull changes greatly: optimized ship has a large width and shallow draft, which can ensure a substantially constant displacement; three cross-sectional line of stem slightly inward depression, leading to thin shape of stem, so that the inlet angle decreases, header wave resistance slows, which help to reduce the wave resistance. Compared with parent ships, it is thinner, which can make the ship having more streamlined feature and help to reduce viscous pressure resistance. Thereby it indicates that the optimization method is reasonable.

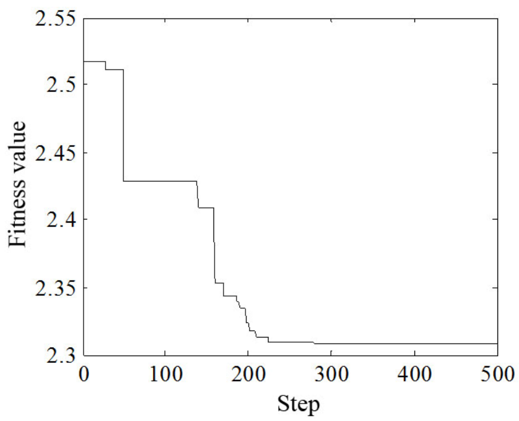

Fig. 7. Iterative curves of optimization

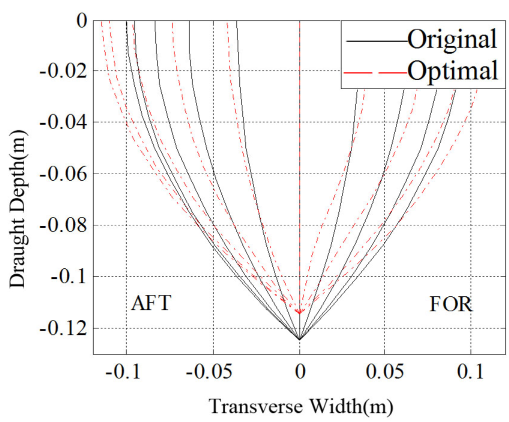

Fig. 8. Section lines of optimal and original

6 Conclusion

In this paper, particle swarm optimization (PSO) algorithm is used instead of rapid descent method of traditional FRBF neural networks to train connection weights, optimizing traditional FRBF training process and proposing FRBF neural network algorithm based on PSO (PSO-FRBF). By comparison and analysis of the wave resistance coefficient of different methods, applicability and superiority of the new algorithm is proved. And PSO-FRBF approximate model of wave resistance is introduced to optimization process based on SBD, obtaining a smooth rational optimization ship, which proved the accuracy of approximate models that established by PSO-FRBF and the feasibility of the main scale ship models' the joint optimization method. The new neural network can provide good technical support for related ship optimization design stage. In the future, the properties of the neural network and applicability of different optimization algorithms are expected to be studied.

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