Research on deep learning method in ship hull form optimization

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ABSTRACT

Waves will cause added resistance and alter the course for a ship. Therefore, this paper presents a multi-objective optimization for ship design in nolinear waves using the Deep Belief Network (DBN) method. The optimization is performed in nolinear waves for the DTMB5512 ship with three variables. The MOPSO is selected as the optimal algorithm. To improve calculation efficiency of the CFD based optimization, a DBN method is proposed to approximate the total resistance coefficient C_{tw} and heave transfer function TF_3 and pitch transfer function TF_5. The optimization results show that the optimization method in this study can optimize the DTMB5512 ship with a reduction in its total resistance and heave and pitch transfer functions. The optimization objective values were reduced about 4.05% and 0.63% and 1.01%, respectively.

Keywords: Ship design optimization, nolinear waves, DBN, MOPSO

1. INTRODUCTION

Computational fluid dynamics (CFD) method is an efficient method calculating the hydrodynamic performance and optimizing different kinds of ships. Zhang et al.[1] utilized the CFD technique to evaluate ship resistance and multi degree of freedom motion parameters and relative rotation diameter, rudder response index and overtaking angle of the surface warship, and then used genetic algorithm to optimize the whole surface warship. Liu et al.[2] used the RANS-VOF and Co-Kriging models to approximate estimate the total resistance of the trimaran, and then utilized the global optimization genetic algorithm to optimize the trimaran shape. Zhang et al.[3] also selected CFD theory to calculate the resistance and wake uniformity for the twin-skeg vessel, and employed the NSGA-II algorithm to find suitable ship geometry meeting the optimal objective. Shang and Zhao[4] used the shipflow method and Kriging model to approximate assessment the wave-making resistance of catamaran, which is used in the wind power operation and maintenance, and selected the global optimization genetic algorithm to optimize the original ship geometry. As can be seen from the above literature, the CFD method has been extensively employed to predict hydrodynamic parameters for different ships. The calculation errors are all within the reasonable range.

With the development of the machine learning approach, many approximate ship hull form optimization techniques have been carried out to optimize the different ship geometry. For example, a maximum entropy adaptive sampling method based on Kriging and UD methods was developed by Ouyang et al.[5] to approximate the drag of S60 ship. Then this method was used to optimize bow and stern section of original ship. Li et al.[6] used a kriging model to calculate the drag and pitch amplitude of the KCS ship, and then selected a multi-objective optimization method to optimize this ship. The results were indicative that the pitch amplitude and average resistance is reduced about 12.7% and 12.5%, respectively. Wang et al.[7] used the double layer feedforward network to calculate the drag of container, and research the relationship between the total resistance and the bulbous bow of this ship. Zhang et al.[8] used a 7500 DWT bulk cargo ship as the optimization objective. They selected BPNN method to predict the resistance of this ship at limit speed, and then the single objective optimization was carried out for this ship.

As can be seen from the above literature, the BP and RBF and Kriging and double layer feedforward network methods have been widely used in the ship optimization, showing good results, while the deep learning method is not studied in the ship-type optimization in recent years. Since the deep learning method has been used in the prediction for different research field, this paper will force on ship design optimization using the deep learning algorithm for purpose of discussing the applicability of this algorithm in the hull optimization field. For this paper, the deep belief network theory is introduced in Section 2. Following this, the CFD technique calculating the hydrodynamic performance of the DTMB5512 ship is shown

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in Section 3, as well as the optimization problem. Next, in Section 4, a multi approximate optimization is carried out, and the optimization results between original and optimal ships have been listed. In the end, the conclusion is listed in Section 5.

2. DEEP BELIEF NETWORK ALGORITHM

The DBN algorithm is a deep learning method, which is constructed with multi-Restricted Boltzmann Machine (RBM) model. The RBM model is trained one by one to obtain the optimal output value. The energy of joint configuration can be calculated using[9]:

$$E(V,H\mid\delta)=-\sum_{i=1}^{n}\sum_{j=1}^{m}V_i w_{ij} H_j-\sum_{i=1}^{n}e_i V_i-\sum_{j=1}^{m}f_j H_j \tag{1}$$

where w_{ij} is connection weights. e_i and f_j are the biases for different layers.

3. SHIP OPTIMIZATION PROBLEMS

3.1 Geometric model

A model-scale of the David Taylor Model Basin (DTMB) 5512 ship was used in this study. It has been widely used for towing tank experiments, numerical simulations and ship hull design optimizations. Figure 1 presents the DTMB5512 ship geometry for the front view.

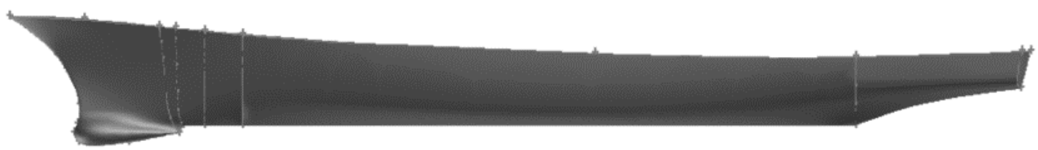

Figure 1. The DTMB5512 ship geometry for the front view.

3.2 CFD approach

The continuity and RANS equations, as well as the Realisable k-ε model were employed in the CFD simulation. A VOF model was applied to simulate the air-water flow with the SIMPLE algorithm. To calculate the heave and pitch motions, two coordinate systems were established. The nolinear waves theory was used to create waves in the inlet boundary. The overset mesh was used to calculate the ship hydrodynamic performance in waves. The size of the background region is $9.84L_{pp}\times3.28L_{pp}\times4.92L_{pp}$, and the overset region is $1.48L_{pp}\times0.16L_{pp}\times0.38L_{pp}$.

3.3 Define optimization problem

The total resistance in waves and heave and pitch motions were selected as optimization objectives. The ship was optimized at design speed (Fr=0.28) with the wave condition λ/L_{pp}=1, ak =0.025. Three design variables are employed in this study to change the original ship for obtaining deformed ship hull. The range of these three parameters were set as-0.3, 0, -0.1, 0.15 and-0.1, 0.15. The MOPSO method is used to find the suitable results in three-dimensional space. The displacement of the deformed ship keeps the same as the original ship by changing the draft. The optimization flowchart can be found in Figure 2. The samples were established first. Then these samples were used to train the DBN model. Finally, the MOPSO algorithm and the trained DBN model were combined to carry out the ship type optimization.

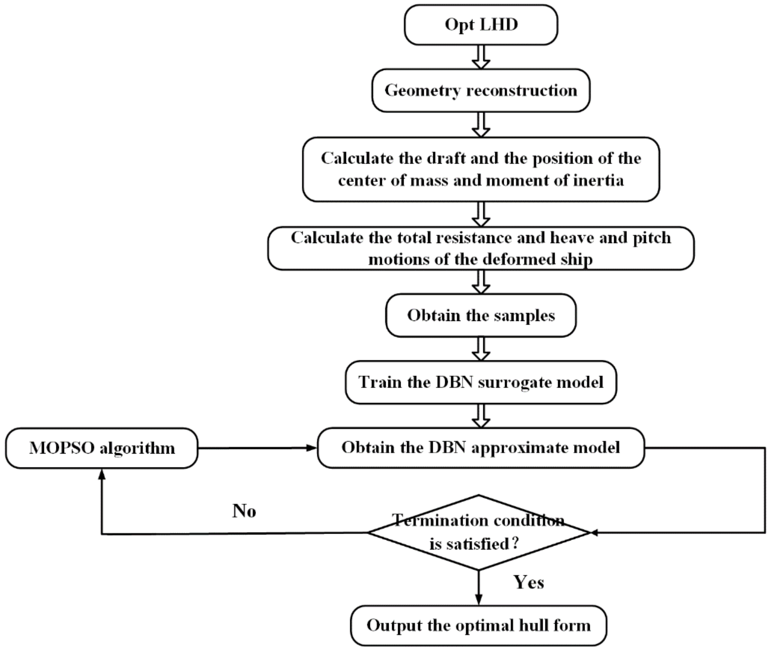

Figure 2. Flow chart of the ship design optimization using the DBN algorithm.

4. RESULTS AND DISCUSSION

4.1 Data preparing and reliability verification

Data preparing is a significant step in order to build a suitable surrogate model. In this study, the Opt LHD method is used to select the samples in the three dimensions space. Table 1 presents the samples and total resistance coefficient C_{tw} and heave transfer function TF_3 and pitch transfer function TF_5. The hydrodynamic parameters (C_{tw} and TF_3 and TF_5) for deformed ships were calculated using CFD method in Section 3.2.

Table 1. Samples obtained by Opt LHD.

No.	a	b	c	C_{tw}	TF_3	TF_5
1	-0.1909	0.1298	0.0742	0.004832	0.56079	0.63944
2	-0.2879	-0.0419	0.0995	0.004723	0.54089	0.62217
3	-0.1485	0.0439	0.0313	0.004853	0.55703	0.63405
4	-0.1939	0.0389	0.1348	0.004817	0.55387	0.62133
5	0	0.0995	-0.0646	0.004862	0.55159	0.62339
…	…	…	…	…	…	…
…	…	…	…	…	…	…
96	-0.2303	0.1424	-0.0066	0.004761	0.55839	0.63783
97	-0.1121	0.0111	0.0818	0.004861	0.56308	0.64615
98	-0.1394	-0.0924	-0.0217	0.004842	0.54131	0.64034
99	-0.0939	-0.0949	0.0894	0.004865	0.54857	0.62743
100	-0.2515	0.1071	0.0465	0.004791	0.55076	0.61025

4.2 Reliability verification

The average relative error e_{avg} and root MAE[10] are used to assessment the accuracy of the data from DBN method. The formulae are defined as:

$$e_{avg}=\frac{1}{n}\sum_{i=1}^{n}\frac{|Q_{i,predict}-Q_{i,CFD}|}{Q_{i,CFD}} \tag{2}$$

$$\text{root} \quad MAE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{i,predict}-Q_{i,CFD})^{2}} \tag{3}$$

where n is equal to 10. $Q_{i,predict}$ is the i-th predicted value calculated by using the DBN approximate model, and $Q_{i,CFD}$ is the i-th true value obtained using the current CFD method.

To obtain suitable approximate model, the 90 samples in Table 1 are employed to build the surrogate model, and remaining 10 samples are selected to validate the accuracy of DBN algorithm. The prediction results of total resistance coefficient C_{tw} and heave transfer function TF_3 and pitch transfer function TF_5 for different methods can be found in Table 2. As shown in Table 2, the value of the e_{avg} and root MAE are very small using the current surrogate model, illustrating the great effectiveness of the DBN algorithm in the prediction of the CFD data. In addition, compared with the prediction results from the root MSE in Reference[10], the current prediction accuracy is higher. Therefore, the current model is used to approximate the total resistance coefficient C_{tw} and heave transfer function TF_3 and pitch transfer function TF_5 in waves.

Table 2. The prediction results for different hydrodynamic parameters using DBN model.

Hydrodynamic parameters	e_{avg}	Root MAE
Total resistance coefficient C_{tw}	0.27%	$1.52*10^{-5}$
Heave transfer function TF_3	0.24%	$1.71*10^{-3}$
Pitch transfer function TF_5	0.22%	$1.57*10^{-3}$

4.3 Discussion of the optimization results

The optimization method shows in Section 3.3 is used to optimize the DTMB5512 ship in nolinear waves with three design variables. The optimization iteration history can be found from Figures 3-5. Figure 3 shows the optimization history of total resistance coefficient C_{tw} for the different deformed ships. Figures 4 and 5 show the optimization history of TF_3 and TF_5. The optimization was carried out for 250 times. This optimization found several feasible solutions. For these feasible solutions, these three objective functions were all decreased.

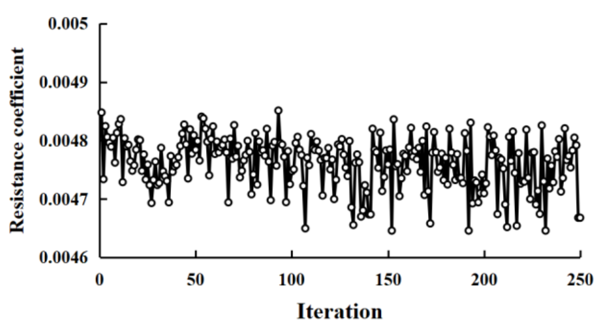

Figure 3. Iteration history for the total resistance coefficients C_{tw}.

To see the optimization results more clearly, the relationship of these three objective values can be found from Figures 6-8, which is also including the pareto front solutions. After the completion of the optimization, the optimal solution is recommended by MOPSO method. The C_{tw} of the optimal ship is reduced about 4.05%, comparing to original ship. Moreover, the heave transfer function TF_3 and pitch transfer function TF_5 of the optimal ship are also lower than the original ship hull, which is good for ship sailing in the sea. The TF_3 and TF_5 are reduced about 0.63% and 1.01% respectively.

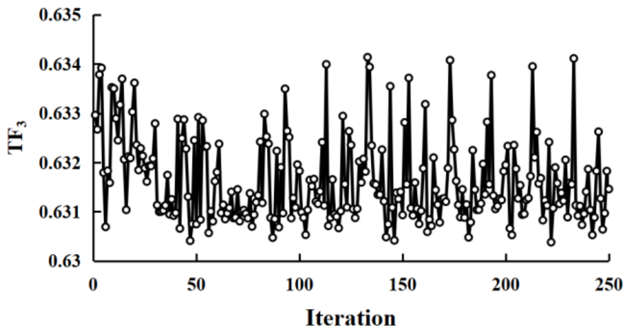

Figure 4. Optimization history for heave transfer function TF_3.

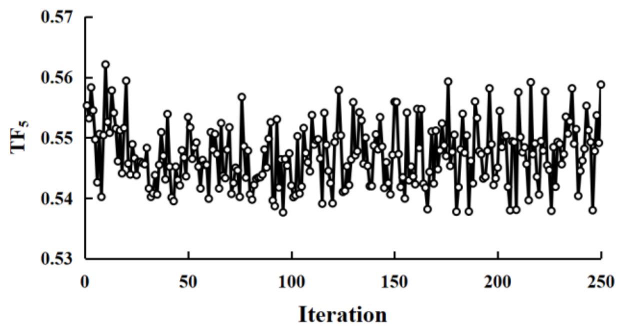

Figure 5. Optimization history for pitch transfer function TF_5.

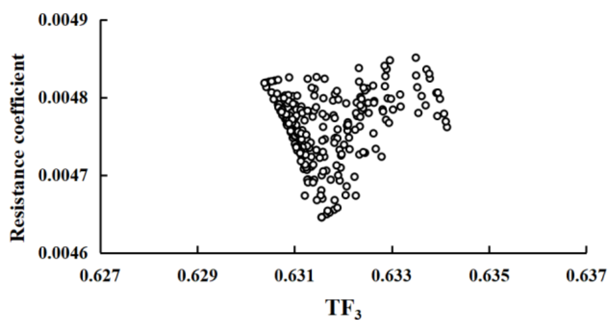

Figure 6. The relationship between TF_3 and C_{tw}.

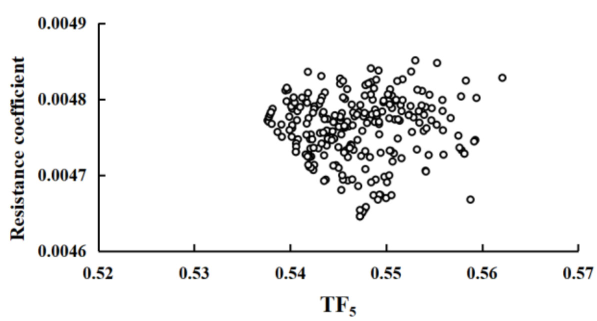

Figure 7. The relationship between TF_5 and C_{tw}.

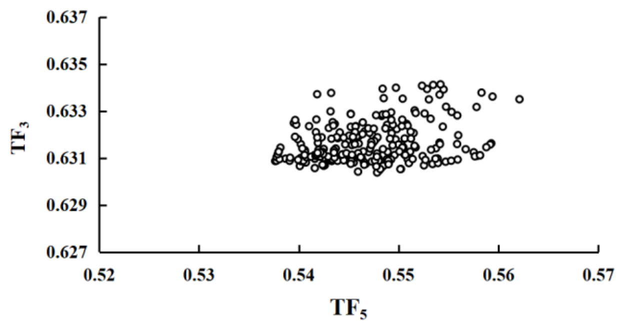

Figure 8. The relationship between TF_5 and TF_3.

5. CONCLUSIONS

By changing the shape of the first half of the DTMB5512 ship, a DBN-based approximate ship type optimization method has been developed for the reduction in total resistance and TF_3 and TF_5 in nolinear waves at design speed using the MOPSO algorithm with three design variables with the wave condition $\lambda/L_{pp} = 1$, $ak = 0.025$. The results show that the hydrodynamic performance (C_{tw} and TF_3 and TF_5) of optimal ship were all reduced. The total resistance coefficients of optimal ship decreased about 4.05%, the heave transfer function of the optimal ship reduced about 0.63% and pitch transfer function decreased by 1.01%.

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REFERENCES

[1] Zhang, H., An, Z. and Song, J., "Research on multi-objective optimization method for ship style decision of surface warship," Ship Science and Technology 44, 34-37 (2022).
[2] Liu, Z., Liu, X. and Wan, D., "Optimization of side hull position for trimaran based on CFD numerical simulation and model test," Shipbuilding of China 63, 116-125 (2022).
[3] Zhang, Q., Jiang, D., Zhang, M. and Fan, T., "Parametric modeling and hull line optimization for twin-skeg vessel," Ship 32, 24-30 (2022).
[4] Shang, Y. and Zhao, L., "Optimization of profile and side-hull spacing of wind turbine operation and maintenance catamaran based on radial basis function," China Offshore Platform 37(1), 70-75 (2022).
[5] Ouyang, X., Chang, H., Liu, Z., Feng, B., Zhang, C. and Cheng, X., "Application of adaptive sampling method in hull form optimization," Journal of Shanghai Jiaotong University 56(7), 937-943 (2022).
[6] Li, L., Wu, J. and Wan, D., "CFD-based optimization for resistance and pitch of KCS ship with appendages in waves," Chinese Journal of Ship Research 17(2), 63-72 (2022).
[7] Wang, C., Chen, W., Du, Y. and Zhang, Q., "Resistance prediction of a container ship improved by sensitivity analysis on characteristic parameters," Journal of Shanghai Ship and Shipping Research Institute 45, 1-9 (2022).
[8] Zhang, W., Zhou, J., Yu, B. and Yu, Y., "Research of model building for bulbous bow resistance optimization based on BPNN," Journal of Dalian University of Technology 61, 160-171 (2021).
[9] Shan, W.,Classification and Recognition of transmission Fault Based on Deep Belief Network,(South China University of Technology, Chapter 2, 10-22 (2015).
[10] Miao, A., Zhao, M. and Wan, D., "CFD-based multi-objective optimisation of S60 Catamaran considering demihull shape and separation," Applied Ocean Research 97, 102071 (2020).