Journal of
Marine Science and Technology

Volume 22 | Issue 6 Article 12

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Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MEST) through GCRC-SOP (No. 2011-0030671), the Industrial Convergence Strategic technology development program (10045212, Predictive maintenance system for the integrated and intelligent operation of offshore plant) funded by the Ministry of Trade, Industry & Energy (MI, Korea), and the Development of vertical-moving derrick system project (No. 10035290) of the funded by the Ministry of Trade, Industry and Energy of Korea.

Journal of Marine Science and Technology, Vol. 22, No. 6, pp. 746-753 (2014)
DOI: 10.6119/JMST-014-0321-12

A STUDY ON OPTIMIZATION OF SHIP HULL FORM BASED ON NEURO-RESPONSE SURFACE METHOD (NRSM)

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Key words: NRSM based optimal design framework, back-propagation neural network (BPN), non-dominated sorting genetic algorithm-II (NSGA-II).

ABSTRACT

Building large and eco-friendly ships has become a clear trend in the ship building industry. Research to minimize ship resistance has actively been investigated for energy savings and environmental protection. However, optimization of the full geometry, while taking into account the hydrodynamic performance is difficult because extensive time is needed to calculate the performance factors, such as the resistance and propulsion. Hence we suggest an optimal design framework based on the neuro-response surface method (NRSM) for optimal shape design in consideration of hydrodynamic performance. The optimization algorithm of the constructed framework consists of the back-propagation neural network (BPN) and the non-dominated sorting genetic algorithm-II (NSGA-II). Using the framework, we performed a case study to optimize the hull form of a 4300TEU container ship with consideration of wave resistance, viscous pressure resistance, and wake fraction.

I. INTRODUCTION

There is a close relationship between the shape and performance of an engineering structure. In the case of ships, hydrodynamic performance parameters such as resistance and propulsion are determined by the hull form. The hull form is determined in the initial design phase, so it is very important to choose a hull form with good performance early on in ship design.

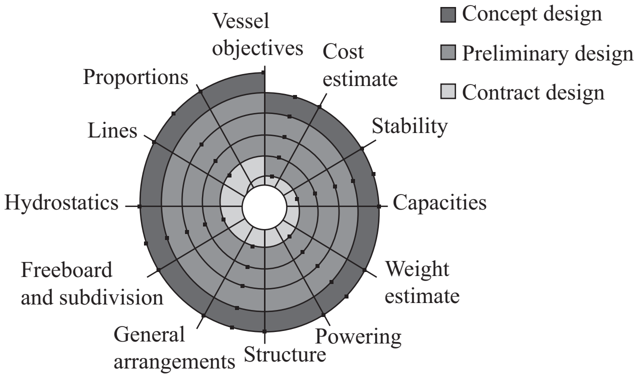

Fig. 1. Traditional design spiral.

Traditional hull form design has produced various candidates which satisfy design criteria through repetitive modification and performance evaluation processes using a design spiral, as illustrated in Fig. 1. The final decision has depended upon the experience of the designer. Revising each step of the process in traditional hull form design is time-consuming. Early prediction of the optimum bow shape considering only wave resistance can be done using theoretical calculations. However, because of turbulent flow, it takes a long time to calculate the viscous resistance and irregular wake distribution, which are linked to the stern shape. So, it is difficult to optimize the hull shape with full consideration of the hydrodynamic performance in a limited time. Therefore a new approach is needed for hull form optimization that considers hydrodynamic performance in the initial design stage.

Many researchers have tried to optimize hull forms based on numerical and experimental methods. Numerical calculation has been performed for hull form design and compared with experimental results. Jung [5] tried to study the prediction method for maneuverability of the KVLCC1's based on experimental and numerical methods. Kim *et al.* [6]

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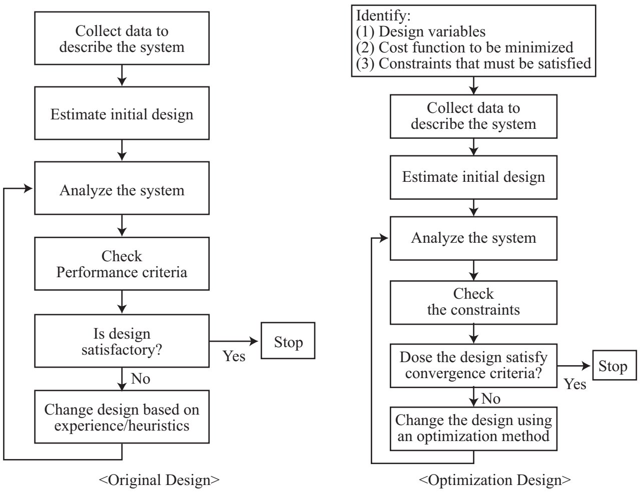


Fig. 2. Original and optimization design process.

developed a framework to optimize the stern form based on CFD. Choi [2] tried to optimize the hull from with a minimum wave resistance, and Yang *et al*. [11] did a wake comparison between model and full-scale ship using CFD. In these studies, CFD calculation was just used to check the hydrodynamic performance of the final design. We cannot find research integrating CFD calculation with viscous flow analysis into the process of hull form optimization.

Major shipyards have constructed many ships worldwide and performed many model tests for their designs, so much experimental performance data for various hull forms is available. Such data has been used for optimum hull form design. We can categorize many studies as data-based optimizations. Shin [10] employed a neuro-fuzzy algorithm to predict the wake distribution. Lee and Choi [8] tried to optimize the hull form using the parametric design method. and Zakerdoost *et al*. [12] tried to reduce the total drag force using evolutionary algorithm.

In this study, we suggested an optimal design framework based on the neuro-response surface method (NRSM) for optimal shape design. The optimization algorithm of the framework consists of the back-propagation neural network (BPN) [4] and the non-dominated sorting genetic algorithm-II (NSGA-II) [3]. The framework was used to optimize a 4300TEU container ship while considering hydrodynamic performance parameters such as the wave resistance coefficient, viscous pressure resistance coefficient, and wake fraction. The results were quantitatively compared with data from SHIPFLOW analysis.

II. OPTIMIZATION FRAMEWORK BASED ON NRSM

The human element often causes erroneous results in the design of complex structures. Thus, consideration of optimization design and minimizing human elements are needed in the design process (Fig. 2) [1].

Table 1. Main dimensions.

LBP	Beam	Draft	Fn
251.7 m	32.2 m	12 m	0.234

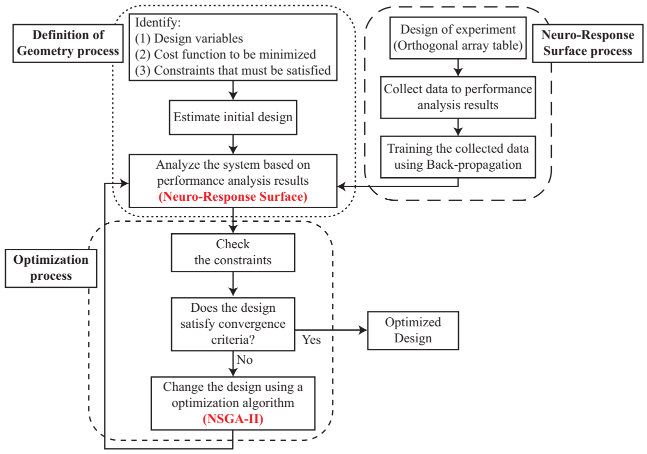


Fig. 3. NRSM based optimal design framework.

The essence of the optimization design process is the performance analysis with different structure shapes. Generally, shape optimization while considering performance is difficult because performance analysis takes a long time for complex engineering structures. We tried to accomplish this using the proposed optimal design framework [7]. The framework consists of three parts which define the shape, generate the design space using the NRSM, and optimize the shape in consideration of its performances (Fig. 3).

The design space is generated using a pre-trained BPN based on model test results or small CFD analysis results, and the optimization process is done in the generated design space. The NSGA-II algorithm is used for multi-objective optimization.

II. CASE STUDY

The applicability of the proposed framework was verified using a 4300TEU container ship optimization problem while taking into account the hydrodynamic performance (wave resistance coefficient, viscous pressure resistance coefficient and wake fraction). The main dimensions of the ship are shown in Table 1.

The initial hull form was obtained using FRIENDSHIP software, which is based on a parametric design method.

The accuracy of the constructed framework results has been analyzed using commercial software (SHIPFLOW).

1. Formulation of Optimization Problem

The formulation process of the optimization problem is presented in Fig. 4.

The equation below represents the optimization formulation for the hull form while considering hydrodynamic performance (Eqs. (1) and (2)).

Table 2. Design variables.

No.	Design variables	
(1)	Bow	Bulb length
(2)		Bulb tip elevation
(3)		Bulb half beam at F.P
(4)		Tangent at bulb tip
(5)		Entrance angle
(6)	Stern	Tangent at Fwd shoulder
(7)		Fullness of FOS at Aft
(8)		Run angle
(9)		Fullness of FOB at Aft
(10)	Full geometry	C_P
(11)		LCB

Table 3. Range of design variables.

Low limit	Design variable	Upper limit
7.0000	Bulb length	9.3099
7.0500	Bulb tip elevation	8.6900
2.2905	Bulb half beam at F.P	2.3893
85.0000	Tangent at bulb tip	100.0000
9.5000	Entrance angle at SAC	12.2300
130.0000	Tangent at Fwd shoulder	140.0000
0.6100	Fullness of FOS at Aft	0.6400
85.0000	Run angle at DWL	95.0000
0.6000	Fullness of FOB at Aft	0.6200
0.6945	C_P	0.6963
123.0000	LCB	123.2386

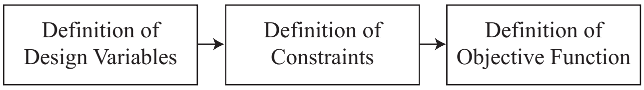


Fig. 4. Formulation process of optimization problem.

Find x_i
where, x_i = Design variables

to minimize

$$F(x) = [f_1(x), f_2(x), f_3(x)] \tag{1}$$

where,
$f_1(x)$ = Wave resistance coefficient (C_W)
$f_2(x)$ = Viscous pressure resistance coefficient (C_{VP})
$f_3(x)$ = Wake fraction

subject to

$$\min x_i \le x_i \le \max x_i \tag{2}$$

i = 1, 2, 3, …, 11 (*number of design variables*)

Eleven design variables were considered, such as the shape of the bow, the shape of the stern, and the full geometry of the hull form. Table 2 presents the selected design variables.

This case study was considered as a side constraint optimization problem. The constraints of each design variable were established in a range that does not degrade the shapes as shown in Table 3.

After choosing the design variables and constraints, the objective functions (C_W, C_{VP}, and wake fraction) to be minimized were established.

Wave resistance coefficient (C_W)

It is assumed that water is a non-viscous and incompressible fluid and that the fluid flow is irrotational. The velocity component of the hull surface was obtained by calculating the flow around the hull form using the Rankine source method, which considers the non-linearity of the free surface boundary condition. The pressure coefficient (C_P) was obtained from Bernoulli's principle, and the wave resistance coefficient was calculated by integration of the pressure coefficient over the hull surface (Eq. (3)).

$$C_W = \int C_P N_X ds / \int ds \tag{3}$$

where,
$\int ds$: wetted surface area
N_X: x component of normal vector of hull surface

Viscous pressure resistance coefficient (C_{VP})

The viscous resistance of the ship can be divided into friction resistance and viscous pressure resistance. The viscous pressure resistance is the drag that results from integration of the component of pressure in the ship heading direction on the hull surface over the wetted surface area. The resistance contributes to a certain part of the 3-D flow separation related to the generation of bilge vortex (Eq. (4)).

$$C_{VP} = \frac{R_{VP}}{(\rho V^2/2)S} \tag{4}$$

where,
R_{VP}: Viscous pressure resistance
V: Ship speed
S: Wetted surface area
ρ: Water density

Wake fraction

The fluid around a ship moves along the same direction as the ship, and this fluid movement is called the wake. The wake increases as it moves from the bow to stern, and the relative velocity of water that goes into the propeller is called the wake fraction. The wake fraction is calculated as follows (Eq. (5)).

Table 4. Orthogonal array table.

Trial no.	Column no.										
	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

Table 5. Performance analysis results.

	Performance analysis results		
	C_W	C_{VP}	Wake Fraction
Case 1	1.1710E-04	2.6960E-04	2.1522E-01
Case 2	5.2020E-05	2.5960E-04	1.9728E-01
Case 3	1.1870E-04	2.6160E-04	1.9619E-01
Case 4	9.0400E-05	2.6930E-04	2.1473E-01
Case 5	6.3400E-05	2.6760E-04	2.1379E-01
Case 6	2.0300E-05	2.7030E-04	2.1089E-01
Case 7	2.2490E-05	2.6770E-04	2.1516E-01
Case 8	-6.9870E-06	2.6700E-04	2.0717E-01
Case 9	5.1400E-05	2.6370E-04	2.0996E-01
Case 10	1.2110E-04	2.6410E-04	2.0972E-01
Case 11	2.7900E-06	2.6270E-04	2.0103E-01
Case 12	9.9650E-05	2.5810E-04	1.9686E-01

$$w = \frac{(V - V_A)}{V} \tag{5}$$

where,
V_A: Propeller forward speed
V: Ship speed
$(V - V_A)$: Wake speed

2. Definition of Hull Form

The geometries of a 4300TEU container ship were defined by parameterization (Table 2). The generated geometries were used for constructing the approximate design space. Twelve sets of design alternatives were generated using an orthogonal array table (OA (12, 2^{11})) [9], as shown in Table 4. The "1" and "2" values in this table are the same as the low limits and high limits of Table 3. Case number 1 is the base design case.

Table 5 shows the results of the performance analysis for the wave resistance coefficient (C_W), viscous pressure resistance coefficient (C_{VP}), and wake fraction using commercial code (SHIPFLOW).

Table 6. Training dataset.

	Training data		
	C_W	C_{VP}	Wake Fraction
Case 1	1.1710E-04	2.6960E-04	2.1522E-01
Case 2	5.2020E-05	2.5960E-04	1.9728E-01
Case 4	9.0400E-05	2.6930E-04	2.1473E-01
Case 5	6.3400E-05	2.6760E-04	2.1379E-01
Case 6	2.0300E-05	2.7030E-04	2.1089E-01
Case 8	-6.9870E-06	2.6700E-04	2.0717E-01
Case 10	1.2110E-04	2.6410E-04	2.0972E-01
Case 11	2.7900E-06	2.6270E-04	2.0103E-01
Case 12	9.9650E-05	2.5810E-04	1.9686E-01

Table 7. Test dataset.

	Test data		
	C_W	C_{VP}	Wake Fraction
Case 3	1.1870E-04	2.6160E-04	1.9619E-01
Case 7	2.2490E-05	2.6770E-04	2.1516E-01
Case 9	5.1400E-05	2.6370E-04	2.0996E-01

Table 8. Structure of the BPN.

Back-propagation neural network		
Input node (n_i)	Hidden node	Output node (n_o)
11	$\sqrt{n_i \times n_o}$	3

After analysis of the generated design cases, we constructed the design space using NRSM. Then, we predicted the performance of the design cases in a continuous design space without direct computing. It is important to generate the design space because the optimization process progresses in the generated design space. Therefore, the generated design alternatives were divided into 2 sets:

- Training data (Table 6): to generate the design surface
- Test data (Table 7): to check the prediction accuracy

3. Generation of Design Space Using NRSM

The multi-layer perceptron (MLP) was used to construct the design space. It has three layers: an input layer, a hidden layer, and an output layer. The back-propagation algorithm was used for training the neural network. We tried to find the best structure and number of learning cycles for the neural network. The number of hidden nodes was defined using the relationships between the input node (n_i and output node (n_o) (Table 8). The final array of neurons and the number of learning cycles were 11-5-3 and 15000, respectively. Fig. 5 shows the error convergence in the learning process of the network. The error convergence is about 0.05 below after 12000 iterations using the constructed framework.

Table 9. Results for BPN training.

	Original values		
	C_W	C_{VP}	Wake Fraction
Case 1	1.1710E-04	2.6960E-04	2.1522E-01
Case 2	5.2020E-05	2.5960E-04	1.9728E-01
Case 4	9.0400E-05	2.6930E-04	2.1473E-01
Case 5	6.3400E-05	2.6760E-04	2.1379E-01
Case 6	2.0300E-05	2.7030E-04	2.1089E-01
Case 8	-6.9870E-06	2.6700E-04	2.0717E-01
Case 10	1.2110E-04	2.6410E-04	2.0972E-01
Case 11	2.7900E-06	2.6270E-04	2.0103E-01
Case 12	9.9650E-05	2.5810E-04	1.9686E-01
	Prediction values		
	C_W	C_{VP}	Wake Fraction
Case 1	1.1069E-04	2.6778E-04	2.1153E-01
Case 2	6.4261E-05	2.5936E-04	1.9464E-01
Case 4	8.8277E-05	2.6824E-04	2.1451E-01
Case 5	4.4247E-05	2.6923E-04	2.1688E-01
Case 6	2.1837E-06	2.6343E-04	2.0273E-01
Case 8	-1.4992E-05	2.6381E-04	2.0761E-01
Case 10	7.8671E-05	2.6709E-04	2.1486E-01
Case 11	1.1790E-05	2.6207E-04	2.0606E-01
Case 12	1.211E-04	2.6016E-04	1.9464E-01

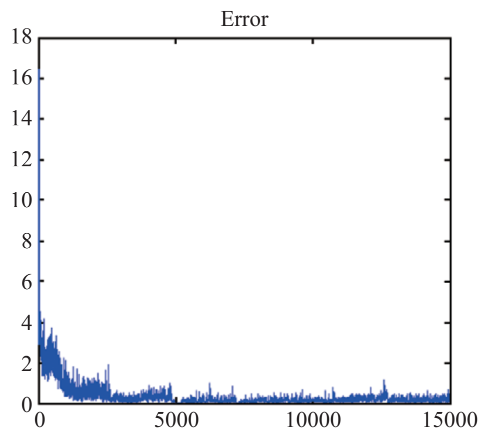


Fig. 5. Error convergence

The error is defined in Eqs. (5) and (6), where "y" and "d" mean the output of the network and the original value. "L" means the number of output neurons and "$E(n)$" is the measure of error.

$$e_n(n) = d_i(n) - y_i(n) \tag{5}$$

$$E(n) = 0.5 \times \sum_{i=1}^{L} e_i^2(n) \tag{6}$$

Table 9 shows the accuracy of the generated design space. In this table, "original values" are the SHIPFLOW analysis results, and "prediction values" are the output of the neural network.

Table 10. Measure of error.

	Measure of error [$E(n)$]		
	C_W	C_{VP}	Wake Fraction
Case 1	4.11E-11	3.31E-12	1.36E-05
Case 2	1.50E-10	5.76E-14	6.97E-06
Case 4	4.51E-12	1.12E-12	4.84E-08
Case 5	3.67E-10	2.66E-12	9.55E-06
Case 6	5.06E-10	4.72E-11	6.66E-05
Case 8	6.41E-11	1.02E-11	1.94E-07
Case 10	7.44E-10	1.15E-11	2.40E-05
Case 11	2.13E-10	3.97E-13	2.53E-05
Case 12	4.60E-10	4.24E-12	4.93E-06
$E(n)$	1.27E-09	4.03E-11	7.56E-05

Table 11. Checking the generated design space.

	Original values		
	C_W	C_{VP}	Wake Fraction
Case 3	1.1870E-04	2.6160E-04	1.9619E-01
Case 7	2.2490E-05	2.6770E-04	2.1516E-01
Case 9	1.2110E-04	2.6410E-04	2.0972E-01
	Prediction values		
	C_W	C_{VP}	Wake Fraction
Case 3	1.3551E-04	2.6259E-04	1.9547E-01
Case 7	2.2633E-05	2.6953E-04	2.1724E-01
Case 9	1.2190E-04	2.6542E-04	2.0951E-01

Table 12. Measure of error.

	Measure of error [$E(n)$]		
	C_W	C_{VP}	Wake Fraction
$E(n)$	1.42E-10	3.04E-12	2.44E-06

Table 10 shows the prediction accuracy of the trained neural network for 9 cases in the training sample. The structure of the neural network is appropriate, because the error values are very small (Table 10).

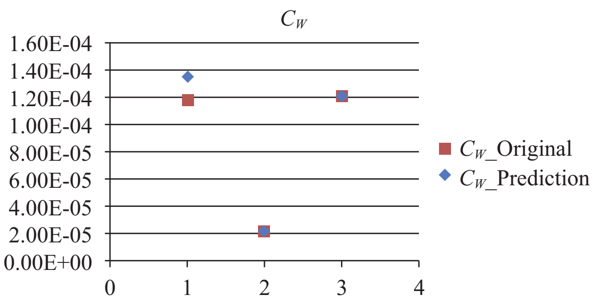
Table 11 shows the prediction accuracy of the trained neural network, and Table 12 and Fig. 6 show the prediction error of the test dataset in the generated design space. In this process, the accuracy of the constructed design space can be checked. Analysis of the results for Table 12 shows that there are still prediction errors. However, in order to predict the performance in a limited time, the neural network can give reasonable results for the design stage.

4. Optimization Process

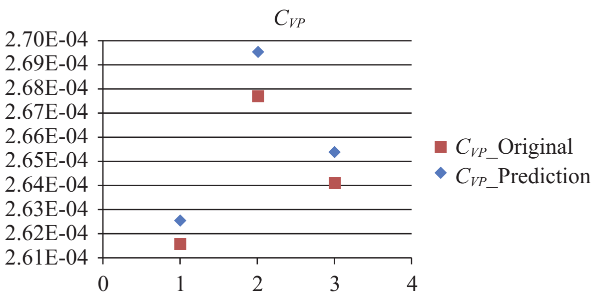
We tried to find the optimum design using NSGA-II in the generated design space. Table 13 and Fig. 7 show the parameters of NSGA-II and the Pareto optimum set as the final result of the optimum design framework. To select the final optimum design among the pareto-optimum set, we used a

Table 13. Parameters of NSGA-II.

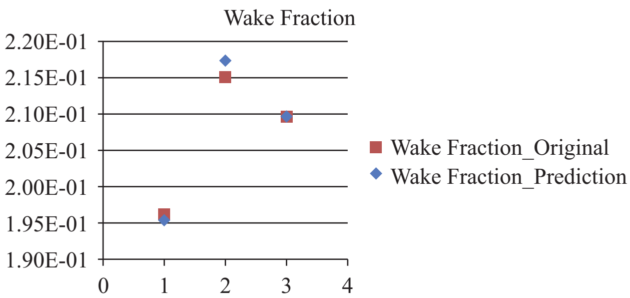
NSGA-II			
Pop-size	Generation	Crossover	Mutation
100	1000	20%	1%



(a) Wave resistance coefficient (C_W)



(b) Viscous pressure resistance coefficient (C_{VP})



(c) Wake fraction

Fig. 6. Accuracy for generated design space.

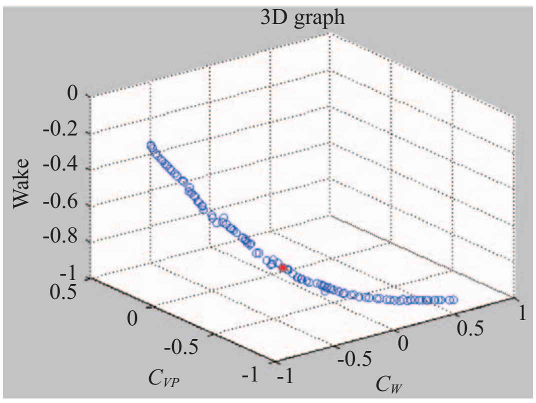


Fig. 7. Pareto optimum set.

Table 14. Design variables.

	Base design	Optimum design
Bulb length	7.0000	8.1715
Bulb tip at bottom	7.0500	7.6217
Bulb half beam at F.P	2.2905	2.3465
Tan. at bulb tip	85.0000	94.8070
Entrance angle at SAC	9.5000	11.5094
Tan. at Fwd shoulder	130.0000	139.3077
Fullness of FOS at Aft	0.6100	0.6390
Run angle at DWL	85.0000	89.1923
Fullness of FOB at Aft	0.6000	0.6173
C_P	0.6945	0.6957
LCB	123.0000	123.2330

Table 15. Performance results.

	Results		
	C_W	C_{VP}	Wake Fraction
Framework	9.4800E-06	2.5912E-04	1.9786E-01
SHIPFLOW	2.7867E-05	2.7300E-04	2.0004E-01

Table 16. Improvement of optimum design case.

Improvement [(Base model – Optimization model)/Base model]		
C_W	C_{VP}	Wake Fraction
23.8% decrease	1.2% increase	7.1% decrease

Table 17. Results for water plane area and efficiency power.

	Original model	Optimized model
Water plane area (m^2)	7075.3770	7195.4950
Effective power (Kw)	1.5539E+04	1.2089E+04

weighting factor of 0.3333 for each objective function (C_W, C_{VP}, and wake fraction). In Fig. 7, the red points represent the selected optimum design case.

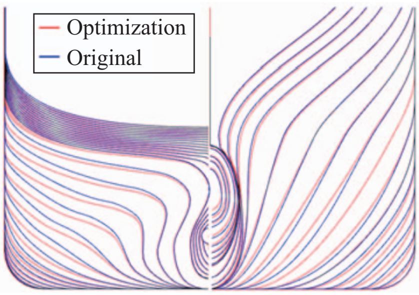
Table 14 shows design variables for the selected optimum design using the optimal design framework.

Table 15 shows the performance analysis results of the obtained framework and SHIPFLOW calculation results. The results of the framework are close to those of SHIPFLOW.

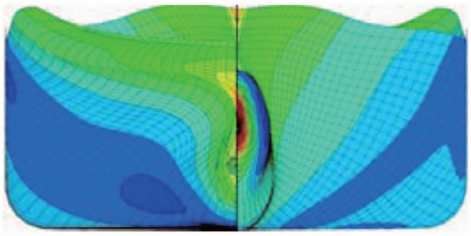
5. Analysis of Optimum Design Case

The improvement for standards of performance evaluation was analyzed using the selected optimum design case. The performance of the optimum hull form is better than that of the original hull form except for the viscous pressure resistance coefficient (Table 16).

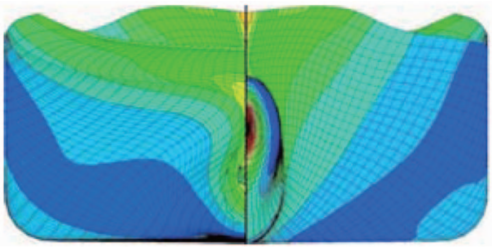
Table 17 presents the waterplane area, which affects stability, and the effective horse power (EHP), which is related to fuel consumption of the target hull form and optimal hull form.



(a) Original and optimized lines



(b) Pressure of original hull form



(c) Pressure of optimization hull form

Fig. 8. Results for original and optimized hull form.

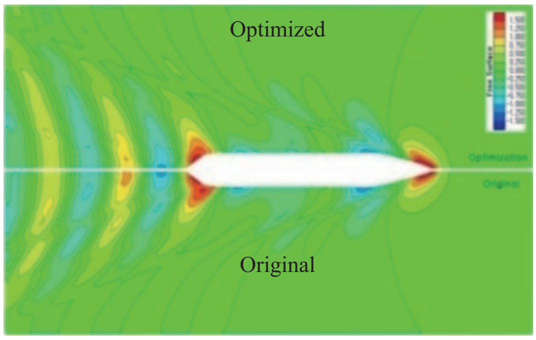


Fig. 9. Free surface wave height.

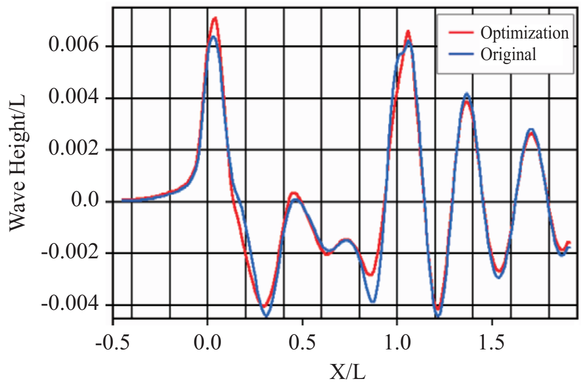


Fig. 10. A comparison between the initial and optimum lines wave cut.

The optimized hull form shows a 1.7% increase in waterplane area and 22% decrease in EHP. These results mean the optimum hull form is better than the original hull form in terms of stability and fuel consumption.

Fig. 8(a) presents a comparison between the target hull form and the optimized hull form. The pressure of both the bow part and stern part (Figs. 8(b) and (c)) and the wave height (Figs. 9 and 10) have been decreased with the optimized hull form.

IV. CONCLUSION

Several conclusions were obtained from this study:

1. The "optimization design framework based on neuro-response surface method (NRSM)" chooses the optimal hull form based on performance. It was constructed using small CFD analysis data acquired in a limited time.
2. An optimal hull form could be generated in limited time by applying the framework to hull form optimization with hydrodynamic performance consideration.
3. Quantitative comparisons between the target hull form and the optimal hull form result are as follows:

   A. The wave resistance coefficient and wake fraction decreased by approximately 23.8% and 7.8%, and the viscous pressure resistance coefficient was increased approximately 1.7%.

   B. The waterplane area for evaluating stability was increased approximately 1.7% compared to the initial value, and EHP was decreased about 22%.

ACKNOWLEDGMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MEST) through GCRC-SOP (No. 2011-0030671), the Industrial Convergence Strategic technology development program (10045212, Predictive maintenance system for the integrated and intelligent operation of offshore plant) funded by the Ministry of Trade, Industry & Energy (MI, Korea), and the Development of vertical-moving derrick system project (No. 10035290) of the funded by the Ministry of Trade, Industry and Energy of Korea.

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