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Study of Trim Optimization Based on Design of Experiments and RANS Simulation

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ABSTRACT

Trim optimization is a particularly easy and cheap way of improving ship performance, reducing fuel oil consumption and lowering emission. The purpose of trim optimization is to obtain the optimal trim to minimize the ship total resistance at the specified draft and speed. The usual approach is to establish a surrogate model to estimate the ship resistance based on some sample points. However, for most of present practices of trim optimization, a large number of sample points are uniformly distributed in the design space composed of draft, trim and speed. As a result, a high computing cost can be expected. In this paper, the design of experiments (DOE) is introduced to reduce the number of sample points. Each sample point contains the ship resistance at a specified draft, trim and speed. Then ordinary kriging interpolation is utilized to construct the surrogate model. The ship resistances at the conditions of the sample points are achieved by Reynolds averaged Navier-Stokes (RANS) simulations and the KCS ship model is selected in the present research. The accuracy of the surrogate model is verified by other RANS simulations. Results indicate that DOE and ordinary kriging interpolation can reduce considerable calls for the CFD solver and remain the accuracy of the surrogate model approximately.

Key words: trim optimization, design of experiments, kriging interpolation, RANS simulations

1 INTRODUCTION

With the increasing environmental pollution, the green ship is gaining more and more attention in the ship industry. The International Maritime Organization (IMO) has issued the relevant regulations and has set the goal of at least 50% reduction of greenhouse gas (GHG) emissions from international shipping by 2050 compared to 2008. Great emphasis is placed on the ship energy efficiency, which directly affects the exhaust emission and fuel bill. Referring to an advisory proposed by the American Bureau of Shipping (ABS), there are various measures to improve the ship energy efficiency, such as hull form optimization, energy-saving device installation, main engine energy efficiency enhancements, weather routing, voyage speed optimization, trim optimization, hull and propeller roughness management and so on [1]. Among these measures, trim optimization is a particularly easy and cheap way of improving ship performance, reducing fuel oil consumption and lowering emission. Trim optimization can be implemented by adjusting the cargo loading and ballast water and there is no need of ship hull modifications, engine upgrade or additional device installation. Generally, 2-3% fuel oil savings can be expected by trim optimization [2].

The prediction of ship resistance is significant in trim optimization and it is mostly based on potential flow theory, computational fluid dynamics (CFD) methods and model tests. Lv et al. [3] developed a surface panel method involving linearized free surface condition and double model solution to predict ship wave resistance under different trim conditions. However, the numerical results of ship wave resistance for the case hull didn't agree well with the experimental results. Shivachev et al. [4] investigated the influence of trim on ship resistance by model tests and numerical computations and the suitability of different CFD techniques are assessed. Results show that both models of fixed hull and heave/pitch free hull could predict the trend of resistance with variation of trim angles, although the fixed ship model failed to predict the ship resistance as accurately as the free ship model did. Reichel et al. [2] investigated the effects of three different experimental methods on the determination of the optimum trim condition and the possible power savings. However, model tests are time and money consuming and the ship resistance prediction based on the potential flow theory are not adequate due to their limited capability to deal with the non-linear free surface and viscous resistance. Therefore, considering both cost and accuracy, the CFD methods are more suitable though they are quite computationally intensive and demanding.

The surrogate model, which is an analytical approximation based on a limited number of sampling points, is introduced. It is quite efficient and effective in engineering optimization [5]. For most of present practices of trim optimization, the sample points are uniformly distributed in the design space composed of draft, trim and speed. As a result, a large number of sample points are required to establish the surrogate model. For example, the trim optimization database for one ship provided by HydrOcean is generated from 100 viscous flow simulations [6]. It is so time and cost consuming that it is worthwhile to explore a way to decrease the amount of computations for most engineering projects.

In this paper, the design of experiments (DOE) is introduced to reduce the cost and time for the trim optimization in calm water by decreasing the calls for the viscid flow solver. DOE aims to explore the design space fully with as few sample points as possible. Latin hypercube sampling (LHS) [7], an approach of DOE, is used to initialize the sample points. Reynolds averaged Navier-Stokes (RANS) simulations are carried out according to the specified conditions of the sample points. The surrogate model is established by means of ordinary kriging interpolation based on ship resistance values of the sample points. The genetic algorithm is utilized to search the optimum trim based on the surrogate model. Four additional simulations are performed to verify the accuracy of the surrogate model. At last, the ship total resistance variations with draft, trim and speed are presented and discussed.

2 METHODOLOGIES

The KRISO (Korea Research Institute of Ships and Ocean Engineering) container ship (KCS) is chosen for the case study, which is one of the benchmark ships within the resistance and maneuvering communities. All simulations are carried out at the 1:31.6 model scale. The related parameters and results are expressed at model scale. The main particulars are listed in Table 1 and the geometry of ship model with rudder is shown in Figure 1.

Table 1: Main particulars of KCS at full and model scale

Parameters	Full scale	Model scale
Scale	1	31.6
L_{PP}(m)	230.0	7.2786
B_{WL}(m)	32.2	1.0190
D(m)	19.0	0.6013
T(m)	10.8	0.3418
∇(m^3)	52030.0	1.6490
S_W(m^2)	9424.0	9.4379
S_R(m^2)	115.0	0.1152
C_B	0.651	0.651
C_M	0.985	0.985
U(m/s, full scale: kn)	24.0	2.196
Fr	0.26	0.26

Figure 1: Geometry of KCS model

Trim is defined as the difference between the draft at FP (T_f) and the draft at AP (T_a). Thus a positive value of trim indicates trim to the bow.

$$Trim = T_f - T_a \tag{1}$$

2.1 Design of Experiments

The design space is defined by the ranges of draft, trim and speed. The draft ranges from 0.2785m to 0.3576 m (Full scale: 8.8 ~ 11.3 m), the trim ranges from -0.0475 m to 0.0475 m (Full scale: -1.5 ~ 1.5 m) and the speed ranges from 1.647 m/s to 2.379 m/s (Fr = 0.195 ~ 0.282). To explore the design space fully with as few sample points as possible, the Latin hypercube sampling (LHS) is used. 16 sample points are initialized in the present research. Therefore, the range of every dimension of the design space is equally divided into 16 portions. A random number is generated in each portion. The sample points are obtained by combining draft, trim and speed values. The constraint is that each random number belongs to exactly one sample point. The 16 sample points are listed in Table 2. Figure 2 presents the positions of 16 sample points in design space.

Table 2: 16 sample points obtained by LHS

Samples	Draft(m)	Trim(m)	Speed(m/s)	Fr
1	0.3244	-0.0231	1.860	0.220
2	0.3292	0.0299	1.700	0.201
3	0.2870	0.0205	1.757	0.208
4	0.3345	0.0467	2.308	0.273
5	0.3148	-0.0068	2.154	0.255
6	0.2826	-0.0372	1.908	0.226
7	0.3026	0.0247	2.344	0.277
8	0.3106	0.0401	1.658	0.196
9	0.3430	-0.0048	1.996	0.236
10	0.3510	0.0164	1.941	0.230
11	0.2954	0.0064	2.238	0.265
12	0.3565	-0.0258	2.285	0.270
13	0.3391	-0.0130	1.806	0.214
14	0.3069	-0.0312	2.069	0.245
15	0.3205	0.0023	2.016	0.239
16	0.2899	-0.0444	2.144	0.254

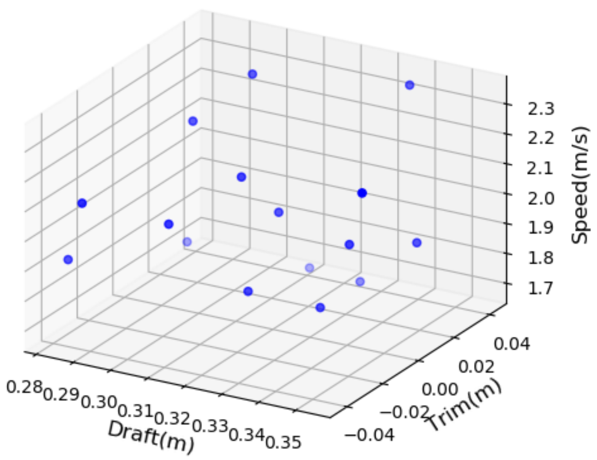

Figure 2: 16 sample points in design space

2.2 Numerical Simulations

The governing equations are the incompressible unsteady RANS equations, as shown in Equation (2). For the closure of RANS equations, the k-ω SST turbulence model is integrated and the equations are shown in Equation (3). The spatial discretization of the equations is completed using the finite volume method. The second-order upwind scheme is employed to discretize the convection terms. The free surface is identified using the two-phase volume of fluid (VOF) method. The simulation is performed with the commercial software FINE™/Marine.

$$\begin{cases} \dfrac{\partial \overline{u_i}}{\partial x_i} = 0 \\ \dfrac{\partial \overline{u_i}}{\partial t} + \dfrac{\partial}{\partial x_j}\left(\overline{u_i} \cdot \overline{u_j}\right) = -\dfrac{1}{\rho}\dfrac{\partial \overline{p}}{\partial x_i} + \upsilon \dfrac{\partial}{\partial x_j}\left(\dfrac{\partial \overline{u_i}}{\partial x_j}\right) + \dfrac{1}{\rho}\dfrac{\partial}{\partial x_j}\left(-\rho\overline{u_i' u_j'}\right) \end{cases} \tag{2}$$

where $\overline{u_i}(i = 1,2,3)$ is the time-averaged components of velocity; ρ is the density; $\overline{p}$ is the mean pressure; υ is the kinematic viscosity; $-\rho\overline{u_i' u_j'}$ is the Reynolds stress.

$$\begin{cases} \dfrac{\partial}{\partial t}(\rho k) + \dfrac{\partial}{\partial x_j}\left(\rho k \overline{u_j}\right) = \dfrac{\partial}{\partial x_j}\left(\Gamma_k \dfrac{\partial k}{\partial x_j}\right) + P_k - Y_k \\ \dfrac{\partial}{\partial t}(\rho \omega) + \dfrac{\partial}{\partial x_j}\left(\rho \omega \overline{u_j}\right) = \dfrac{\partial}{\partial x_j}\left(\Gamma_\omega \dfrac{\partial \omega}{\partial x_j}\right) + P_\omega - Y_\omega + D_\omega \end{cases} \tag{3}$$

where k is the turbulent kinematic energy; ω is the turbulence frequency; Γ_k and Γ_ω represent the effective diffusivity of k and ω, respectively; P_k and P_ω represent the rate of production of k and ω, respectively; Y_k and Y_ω represent the rate of dissipation of k and ω, respectively; D_ω is the cross-diffusion term.

The computational domain shown in Figure 3 is set as a box with the size of $6L_{PP} \times 2L_{PP} \times 2L_{PP}$. Only half of the KCS model is simulated considering the symmetry of the ship. The inlet is $1.5L_{PP}$ ahead of the bow and the outlet is $3.5L_{PP}$ behind the stern. The distance from the baseline of ship model to the top and bottom face is $0.5L_{PP}$ and $1.5L_{PP}$, respectively. The boundary conditions of the top and bottom are set as “updated hydrostatic pressure”. The boundary conditions of the inlet, outlet and side are set as “far field”. The boundary layers are modelled by wall functions and the y+ values are about 150.

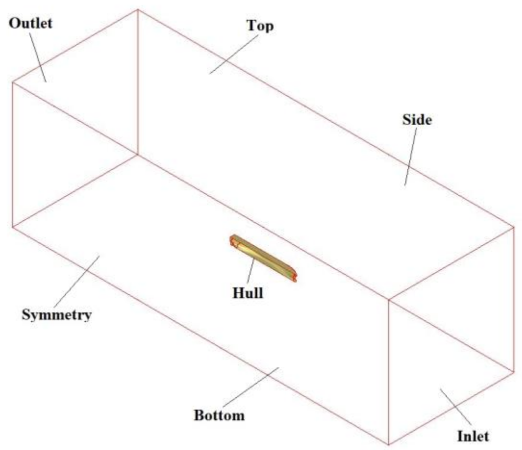

Figure 3: The computational domain

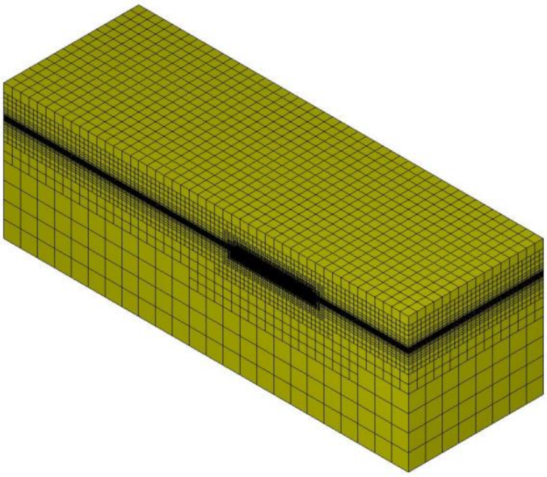

Figure 4: The medium grid

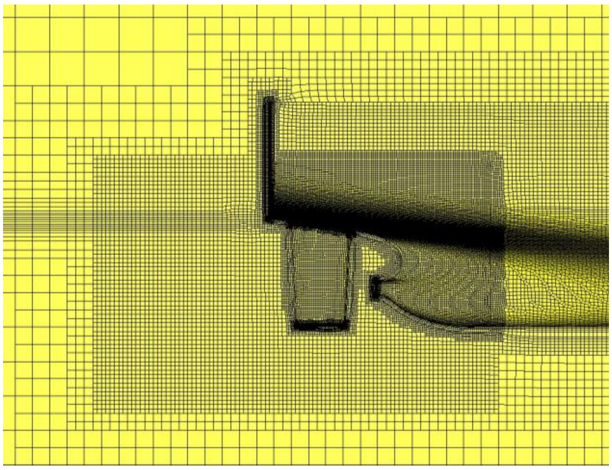

Figure 5: Mesh refinement around the stern

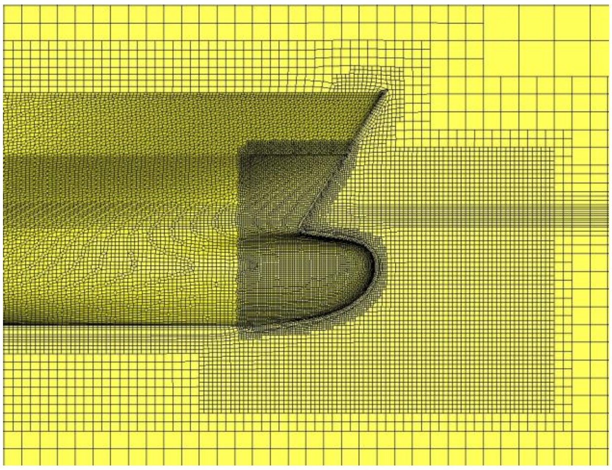

Figure 6: Mesh refinement around the bow

Three grids are utilized to analyze the grid dependency. The coarse, medium and fine grids have 0.7M, 1.9M and 4.2M cells, respectively. The medium grid is shown in Figure 4. Refinements around the bow and stern are adopted, as shown in Figure 5 and 6. The refinement in z direction equals $L_{PP}/1000$ for the free surface. The simulations are performed with the three grids at the designed condition. The resistance coefficient of the ship model is given in Table 3. All the results of different grids agree well with the experimental data from Tokyo 2015 CFD Workshop in ship hydrodynamics, although the error of the coarse grid is slightly larger. Considering the computation accuracy and cost, the same mesh setup as the medium grid is adopted when regenerating grids at different draft and trim conditions. The ship model is free to heave and pitch in each simulation.

Table 3: Cell numbers and computational results of the three grids

Grids	Cells	$1000C_T$	Errors (%)
Coarse	0.7M	3.739	0.76
Medium	1.9M	3.695	-0.43
Fine	4.2M	3.691	-0.53

2.3 Ordinary Kriging Interpolation

To establish the surrogate model, the ordinary kriging interpolation is used. The basic idea is to estimate the resistance of one unknown point by the weighted average of the resistances of sample points. The weight of each sample point depends on the distance between the unknown point and the sample point and the value of the variogram. The variogram model is simplified to linear model in this paper. The implementation of ordinary kriging interpolation is based on PyKrige [8], a kriging toolkit for python.

The sample points are denoted as x_1, x_2, …, x_{16} and $R(x_i)$ (i = 1, 2, …, 16) represents the ship resistance of the point x_i. x_0 is assumed to be the interested point and its unknown resistance is $R(x_0)$. According to the ordinary kriging interpolation, $R(x_0)$ is the weighted average of $R(x_i)$ (i = 1, 2, …, 16), as shown in Equation (4). The weight λ_i (i = 1, 2, …, 16) is decided by Equation (5).

$$R(x_0) = \sum_{i=1}^{16} \lambda_i R(x_i) \tag{4}$$

where λ_i (i = 1, 2, …, 16) is the weight of the point x_i.

$$\begin{bmatrix} \gamma(x_1,x_1) & \gamma(x_1,x_2) & \cdots & \gamma(x_1,x_{16}) & 1 \\ \gamma(x_2,x_1) & \gamma(x_2,x_2) & \cdots & \gamma(x_2,x_{16}) & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \gamma(x_{16},x_1) & \gamma(x_{16},x_2) & \cdots & \gamma(x_{16},x_{16}) & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_{16} \\ -\mu \end{bmatrix} = \begin{bmatrix} \gamma(x_1,x_0) \\ \gamma(x_2,x_0) \\ \vdots \\ \gamma(x_{16},x_0) \\ 1 \end{bmatrix} \tag{5}$$

where $\gamma(x_i, x_j)$ (i = 1, 2, …, 16; j = 0, 1, 2, …, 16) is the variogram value of the points x_i and x_j.

2.4 Genetic Algorithms

To obtain the minimum total resistance in design space, the genetic algorithm is implemented based on the Distributed Evolutionary Algorithms in Python (DEAP) package [9]. The optimization objective is to minimize the total resistance of the KCS model in the aforementioned design space. The fitness value of the individual is set as the ship resistance. The crossover possibility and mutation possibility is set as 0.5 and 0.1, respectively. Each generation has the population of 1000 points. The results converge after 50 generations.

3 RESULTS

The result of the genetic algorithm indicates that the ship resistance reaches the minimum value of 41.69N when draft equals 0.3075 m, trim equals 0.0222 m and speed equals 1.647 m/s. Another RANS simulation at the same condition is performed to verify it and the predicted resistance is 42.49N. The error of the surrogate model relative to the RANS simulation result is -1.88% and it is accepted in engineering.

To verify the accuracy of the surrogate model further, three additional simulations are performed. The draft and the Froude number (Fr) are kept 0.3 m and 0.227 constant, respectively. The trim takes the value of -0.0317 m, 0 m and 0.0317 m in turn. The parameters and results are listed in Table 4. The errors of the surrogate model can be neglected when trim is -0.0317 m and 0 m. However, the error for trim of 0.0317 m is 7.20%. A possible reason is that the point is far away from the nearest sample point and the trim has a strong non-linear influence on ship resistance. Adding more sample points may improve the accuracy. Generally, the surrogate model can predict the total resistance of the KCS model accurately. The wave profiles of the KCS model in different trimmed conditions at draft of 0.3m at Fr of 0.227 are shown in Figure 7. It can be seen that the wave profiles in different trimmed conditions are quite different near the bow and stern, therefore trim can influence the wave resistance of the KCS model.

Table 4: Parameters and results of verification cases

Cases	Draft (m)	Trim (m)	Fr	R_OKI (N)	R_CFD (N)	Errors (%)
1	0.3	-0.0317	0.227	57.50	57.50	0.00
2	0.3	0	0.227	56.08	56.50	-0.74
3	0.3	0.0317	0.227	59.51	55.51	7.20

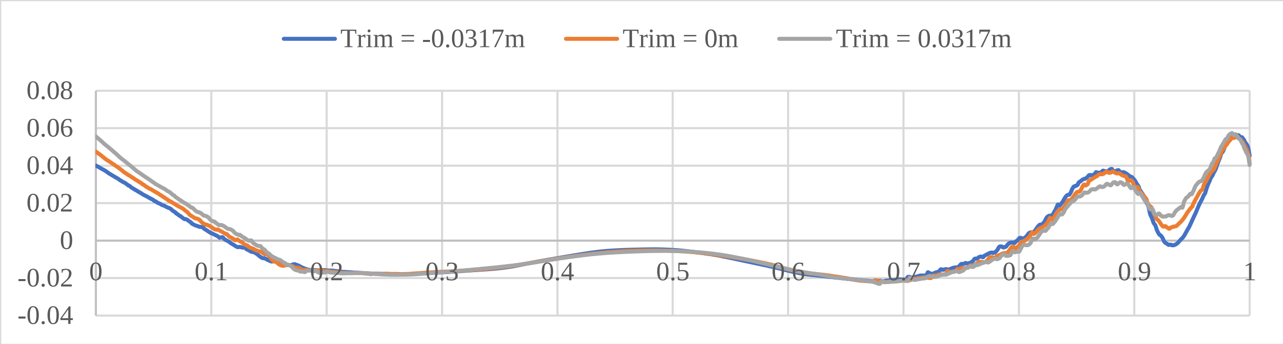

Figure 7: Wave profiles at different trim conditions (draft = 0.3m, Fr =0.227)

After completing the surrogate model, the ship resistance at the given draft, trim and speed can be predicted easily. Figure 8 shows the influence of Fr on ship resistance at draft of 0.3/0.3418 m for trim of 0 m. The ship resistance is approximately proportional to the square of speed. Figure 9 shows how the ship resistance changes as the trims varies from by stern to by bow at draft of 0.3418 m (the design draft) and Froude numbers equal 0.195, 0.227 and 0.260, respectively. The optimal trim is near the even keel condition for all the three Froude numbers and the resistance changes quite gently near the even keel condition. Figure 10 shows the influence of trim and draft on ship resistance at Fr of 0.227. The red line in Figure 10 represents the optimal trim for each draft. The influence of draft and Froude number on the optimum trim is depicted in Figure 11. Three Froude numbers of 0.195, 0.227 and 0.260 are chosen. As the draft increases, the optimal trim transfer from the stern to bow at higher Froude numbers. However, the optimal trim at Fr of 0.195 keeps positive in the full range of draft.

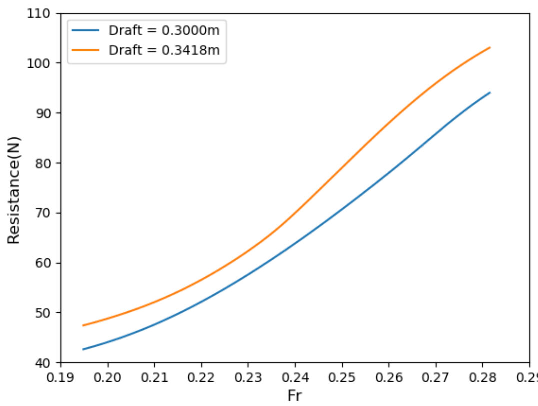

Figure 8: The influence of Fr on ship resistance (trim = 0 m)

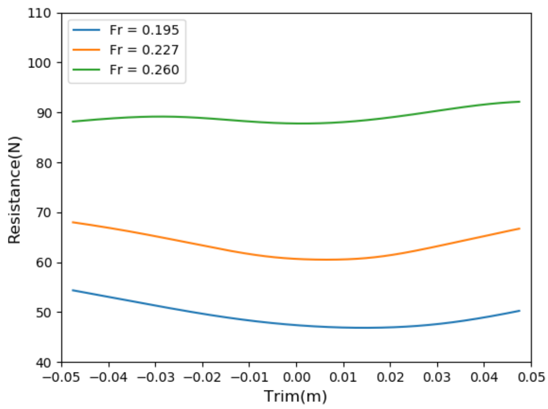

Figure 9: The influence of trim on ship resistance (draft = 0.3418 m)

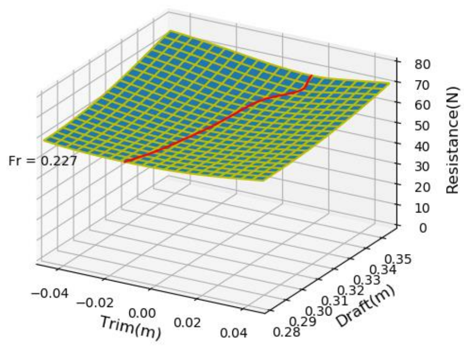

Figure 10: The influence of trim and draft on ship resistance (Fr = 0.227)

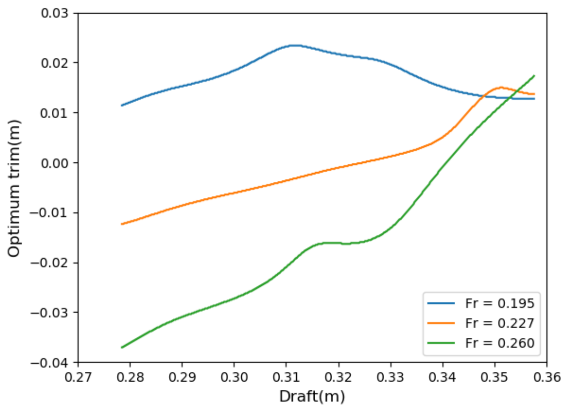

Figure 11: The influence of draft and Froude number on the optimum trim

4 CONCLUSION

This paper presents our first try of combining DOE and ordinary kriging interpolation in ship trim optimization. The DOE is used to obtain the sample points to explore the design space composed of draft, trim and ship speed. RANS simulations are performed to calculate the resistance of KCS model under conditions of these sample points. Ordinary kriging interpolation helps establish the surrogate model to predict ship resistance of other interested points in the design space. The minimum total resistance and its corresponding draft, trim and speed are searched by the genetic algorithm. Additional RANS simulations are carried out to verify the accuracy of the surrogate model. Several conclusions are drawn according to the present results:

(1) The relative error of the minimum resistance between the surrogate model and the RANS simulation is -1.88%. Therefore, the surrogate model has a reasonable accuracy.
(2) Three additional RANS simulations are carried out for verification. Although errors of two cases can be neglected, the error of the third one is up to 7.2%. A possible reason is the strong non-linear influence of trim on ship resistance.
(3) Based on the present approach, trim by bow can reduce the resistance at low Froude numbers. However, as the increase of the Froude number, the minimum resistance tends to be achieved by trim by stern.

It is believed that adding more sample points can improve the accuracy of the present surrogate model. Wave added resistance is also an important topic for trim optimization, which is not considered for now due to the extremely high computing cost. These will be our future work.

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