Comparative Study of Hull Form Optimization with or without Design-Space Dimensionality Reduction

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ABSTRACT

For a hull form optimization design with a relatively large number of design variables, numerous new sample hulls need to be evaluated which cause plenty of computation resource. Therefore, in order to avoid high-dimensional sampling, a design-space dimensionality reduction method based on Proper Orthogonal Decomposition is implemented while retaining the geometric variation in the original design space as much as possible. The Wigley hull is considered as the initial ship in this paper. After the hull form deformation in the original design space is set, the design-space dimensionality reduction is carried out and a new, lower-dimension design space can be obtained. Finally, a comparative study of total drag optimization with or without design-space dimensionality reduction is given by doing several optimizations using OPTShip-SJTU. The optimal hulls are further validated by high-fidelity CFD solver nae-FOAM-SJTU, showing that doing the design-space dimensionality reduction can reduce computation costs while giving relatively good optimization results compared to those in the original high-dimension design space.

KEY WORDS: Design-space dimensionality reduction; Proper Orthogonal Decomposition; Hull form optimization; Total drag; OPTShip-SJTU.

INTRODUCTION

In the past few years, huge development of computer technology and calculation theories allow us to do the Simulation-Based-Design (SBD) other than use empirical or semi-empirical formulas to optimize a ship hull form in order to improve its comprehensive hydrodynamic performances. It is a new design method which integrates hull form modification method, numerical simulation tool and optimization technology. For instance, Campana, Peri, Tahara, and Stern (2006) used the Non-Uniform Rational B-Spline (NURBS) surface modeling method to modify a bulbous bow, and the modified hulls were evaluated by RANS-based solver, and the bulbous was optimized; Yang and Huang (2016) used surrogate models to perform three optimization cases and were validated by cross validation, where each sample point was evaluated from the surrogate model constructed by the rest of the sample points; considering uncertainty, Liu, Wang, and Wan (2018) gave a probability optimization of KCS hull's resistance at full speed range. As mentioned above, researches have focused on the hull form modification, hydrodynamic evaluation, surrogate model construction, and optimization algorithms in the field of hull form optimization.

However, for a hull form optimization design with plenty of design variables, in order to ensure the optimization fidelity, numerous new sample hulls need to be evaluated which cost too much computational resource often. Therefore, in order to avoid high-dimensional sampling, dimensionality reduction is needed and sometimes vital. The so-called dimensionality reduction is the study of reducing the number of variables that define a certain system. This technique can be typically divided into two kinds, feature selection and feature extraction. For the former one, it involves selecting a subset of variables, typically those who have the greatest influence on the output. For the latter one, however, it transforms the old, higher dimensional variables into a new set of lower dimensional variables by analyzing the data.

The Proper Orthogonal Decomposition (POD), also known as Karhunen–Loève Expansion (KLE) or Principal Component Analysis (PCA) can be used for implementing design-space dimensionality reduction to save computational costs, which is a method of feature extraction (Sorzano, Vargas, and Montano, 2014). Regarding the hull form deformation as a linear (or nonlinear) system, the approach is based on the original shape modification space. The selection of a set of orthogonal bases, which are used for a reduced-dimensionality linear representation of the original design space, is the most important part of the dimensionality reduction since it’s quite obvious that if the number of bases is reduced, the dimensionality of the space will be decreased at the same time. Here, the design space is usually assumed to be stochastic because the optimal shape is unknown and we have no idea which part of design space is more important, and only a series of modified hull shapes corresponding to the design variables’ values sampled are needed.

Many researches have proposed a series of dimensionality reduction methods (Danny, Serani, Campana, and Diez, 2017; Diez, Campana, and Stern, 2015; Raghavan, Breitkopf, Tourbier, and Villon, 2013), and
given some applications on hull form optimizations (Chen, Diez, Kandasamy, Zhang, Campana, and Stern, 2015; Danny, Serani, and Diez, 2020; Gaggero, Vernengo, Villa, and Bonfiglio, 2019; Serani, Danny, Campana, and Diez, 2019). However, few of them have given specific mathematical expressions and dimensionality reduction operation procedure in a practical way. Furthermore, during and after the dimensionality reduction, there remain some problems that to be solved or noticed, such as the choice of sum of dense sampling points, the constraints among the new design variables, etc.

In this study, the Wigley hull is considered as the initial hull. The hull form can be globally deformed by shifting method and locally deformed by Radius Basis Function (RBF) method in order to generate a bulbous bow. After the hull form deformation in the original design space is set, the design-space dimensionality reduction is carried out and new, lower-dimensional design spaces can be obtained. Furthermore, giving answers to the questions mentioned above is the main purpose of the work. Finally, a comparative study of total drag optimization with or without design-space dimensionality reduction is given by doing several optimizations using OPTShip-SJTU. The optimal hulls are further validated by high-fidelity CFD solver nae-FOAM-SJTU, showing that doing the design-space dimensionality reduction can reduce computation costs while giving relatively good optimization results compared to those in the original high-dimension design space.

The whole optimization process is implemented using the in-house solver OPTShip-SJTU, which is based on C++ language for the ship hull form optimization. The structure of the OPTShip-SJTU solver is shown in Fig. 1.

![Fig. 1 Framework diagram of OPTShip-SJTU](Image)

**DIMENSIONALITY REDUCTION THEORY**

**Proper Orthogonal Decomposition (POD) for Hull Form Deformation**

The snapshots of the new(deformed) sample hulls \( \chi_i, i=1,2,\ldots,N \) with a total number \( N \), can be got by extracting the coordinates of the mesh points, each of which can be written as a vector of 3*Np* dimensionality, \( x_i^T = (x_i, y_i, z_i, x_i', y_i', z_i', \ldots, x_{Np}, y_{Np}, z_{Np}) \), where \( Np \) is the total mesh point number. The most important thing is to determine the bases, that is to say, the dimension of the hull form (linear) transformation.

It is obvious that each new sample hull can be regarded as the linear combinations of hull bases (with a dimension of positive infinity). For a set of new hulls, use their average hull shape \( \bar{x} \) to represent the variation:

\[
x_i = \bar{x} + \sum_{j=1}^{M} a_{ij} u_j
\]

where \( a_{ij} = (x_i - \bar{x})^T u_j, \quad (u_i, u_j) = \delta_{ij} \cdot \)

Let the dimension be \( M \) with their corresponding basis \( u_1, u_2, \ldots, u_M \), then the reconstruction of the new sample hulls can be written as

\[
x_i^{\text{rec}} = \bar{x} + \sum_{j=1}^{M} a_{ij} u_j
\]  \hspace{1cm} (2)

Consider the total error of the real and the reconstructed new sample hulls \( E_u(u_1, u_2, \ldots, u_M) \):

\[
E_u(u_1, u_2, \ldots, u_M) = \sum_{i=1}^{N} \left| \| x_i - x_i^{\text{rec}} \| \right|^2
\]

where \( \| \cdot \| \) is the usual Euclid norm, and we can easily get

\[
E_u(u_1, u_2, \ldots, u_M) = \sum_{i=1}^{N} \left( \sum_{j=1}^{M} a_{ij} u_j \right)^T \left( \sum_{j=1}^{M} a_{ij} u_j \right) - 2 \sum_{i=1}^{N} (\bar{x} - \bar{x})^T \left( \sum_{j=1}^{M} a_{ij} u_j \right)
\]  \hspace{1cm} (3)

For analytical purposes, the error can be regarded as the sum of three parts shown above. For a given series of new hulls, \( E_1 \) is a const. Now consider the rest two terms:

\[
E_2 = \sum_{i=1}^{N} \sum_{j=1}^{M} (x_i - \bar{x})^T (x_i - \bar{x}) u_j
\]

\[
E_3 = -2 \sum_{i=1}^{N} (x_i - \bar{x})^T \left( \sum_{j=1}^{M} (x_i - \bar{x}) u_j \right)
\]

Therefore, the total error is

\[
E_u = E_1 + E_2 + E_3
\]

\[
E_u = \sum_{i=1}^{N} \left| x_i - x_i^{\text{rec}} \right|^2 + \sum_{j=1}^{M} u_j^T \left( \sum_{i=1}^{N} (x_i - \bar{x}) (x_i - \bar{x})^T \right) u_j
\]  \hspace{1cm} (4)

Recording the difference (disturbance) between each new hull and the average hull \( \bar{x} = x_i - \bar{x} \), and define matrix \( \tilde{X} = (x_1, x_2, \ldots, x_N) \), then

\[
\tilde{X}^T \tilde{X} = (\tilde{x}_1 \tilde{X}^T \tilde{x}_N) = \sum_{i=1}^{N} (x_i - \bar{x})^T (x_i - \bar{x})^T
\]  \hspace{1cm} (5)

So the total error can be rewritten as

\[
E_u = \sum_{i=1}^{N} \left| x_i - x_i^{\text{rec}} \right|^2 - \sum_{j=1}^{M} u_j^T \tilde{X}^T \tilde{X} u_j
\]  \hspace{1cm} (6)

Suppose \( M \) is confirmed, a constrained optimization problem of bases \( u_1, u_2, \ldots, u_M \) can be formulated:

\[
\min E_u(u_1, u_2, \ldots, u_M) = \sum_{i=1}^{N} \left| x_i - x_i^{\text{rec}} \right|^2 - \sum_{j=1}^{M} u_j^T \tilde{X}^T \tilde{X} u_j
\]

s.t. \( u_j^T u_j = 1 \) \hspace{1cm} (7)

Using the Lagrange Multiplier method, we introduce a series of new variables \( \lambda_1, \lambda_2, \ldots, \lambda_M \) called Lagrange multipliers and study the Lagrange function defined by

\[
L(u_1, u_2, \ldots, u_M, \lambda_1, \lambda_2, \ldots, \lambda_M) = E_u - \sum_{j=1}^{M} \lambda_j (1 - u_j^T u_j)
\]  \hspace{1cm} (8)

To find the minimum of the Lagrange function, let
\[ \frac{\partial L}{\partial u_j} = 0 \]  
and we can obtain
\[ \hat{X} \hat{X}^T u_j = \lambda_j u_j \]  
(13)

That is to say, the bases should be the eigenvectors of the matrix
\[ S = \hat{X} \hat{X}^T \in \mathbb{R}^{n \times n} . \]
Commonly, \( 3n_p \) is larger than the number of new sample hulls for high calculation fidelity. In order to find the eigenvectors of \( S \), we can find the singular value decomposition of \( \hat{X} : \)
\[ \hat{X} = UDV^T = \sigma_i u_i v_i^T + \sigma_i u_i v_i^T + \cdots + \sigma_i u_i v_i^T \]
(14)
where \( \sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n > 0 \), then it's quite easy to obtain
\[ \hat{X} \hat{X}^T u_j = (UDV^T U)^T u_j = \sigma_j^2 u_j \]  
(15)

According to Eq. 15, the basis \( u_i \) is just the \( j \)-th row of matrix \( U \) obtained by the singular value decomposition of \( \hat{X} \).

However, we haven’t decided the dimension \( M \) yet. From the perspective of energy, that is, to retain the geometric variation controlled by any values of design variables in the original design space. The energy contained in the basis \( u_j \) is the sum of the square of the length of the projection of each new hull (vector) on basis \( u_k \):
\[ \sum_{j=1}^{m} \left( \langle \tilde{x}_j , u_j \rangle \right)^2 = \sum_{j=1}^{m} \left( \sum_{i=1}^{n} a_{ij} u_{ij} \right)^2 = \sum_{i=1}^{n} a_{ii}^2 = \sigma_i^2 \]  
(16)

From the Eq. 16, it is obvious that the energy is just the eigenvalue of \( S \). Therefore, the energy ratio criteria can be defined by
\[ E_n = \frac{\sum_{i=1}^{M} \sigma_i^2}{\sum_{i=1}^{n} \sigma_i^2} \times 100\% \]  
(17)

Furthermore, \( M \) can be the minimum integer when \( E_n \geq 95\% \). In this situation, we say that the eigenvectors corresponding to the first \( M \) maximum eigenvalues of matrix \( S \) carry 95\% of the energy of the entire hull form deformation range.

After obtaining the new dimensionality-reduced design space via the bases, any new hull form deformed through several kinds of methods (FFD, RBF, etc.) can be reconstructed by
\[ x_i^{new} = \overline{x} + \sum_{j=1}^{M} a_{ij} u_j \]  
(18)
where \( a_{ij} = \langle x_i - \overline{x} , y_j \rangle u_j = \overline{x}_{ij} u_j \)

From Eq. 18, the new design variables’ ranges can be estimated by
\[ a_{ij} \in [\min_{x \in X} (x_i - \overline{x})^T u_j , \max_{x \in X} (x_i - \overline{x})^T u_j ] , i = 1,2, \cdots , N; j = 1,2, \cdots , M \]  
(19)
However, there may be mutual constraints among the new design variables which should be considered while doing the optimization.

APPLICATION ON THE HULL FORM TOTAL DRAG OPTIMIZATION

Take the Wigley hull as the initial hull form, whose main dimensions can be seen in Table 1, and two views of the model can be seen in Fig. 2.

After generating a bulbous bow by deforming the NURBS surface using RBF method, a fundamental optimization case is set according to Liu, Wan, Chen, and Hu (2019) where details of each module can be seen.

We firstly select 7 design variables, including four by shifting method at the fore and aft parts and other three for changing the shape of the bulbous bow by altering the two control nodes (\( P_1 \) and \( P_2 \)) shown in Fig. 3.

<table>
<thead>
<tr>
<th>No.</th>
<th>Method</th>
<th>Node/Region</th>
<th>Design Variables</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RBF</td>
<td>( P_1-x )</td>
<td>( x )</td>
<td>[ 0.515, 0.545 ]</td>
</tr>
<tr>
<td>2</td>
<td>RBF</td>
<td>( P_1-z )</td>
<td>( z )</td>
<td>[-0.049, -0.0344 ]</td>
</tr>
<tr>
<td>3</td>
<td>RBF</td>
<td>( P_2-y )</td>
<td>( y )</td>
<td>[ 0.005, 0.021 ]</td>
</tr>
<tr>
<td>4</td>
<td>Shifting</td>
<td>Region1</td>
<td>( \alpha_1 )</td>
<td>[-0.02, 0.02 ]</td>
</tr>
<tr>
<td>5</td>
<td>Shifting</td>
<td>Region2 (fore part)</td>
<td>( \alpha_2 )</td>
<td>[ 0.2, 0.3 ]</td>
</tr>
<tr>
<td>6</td>
<td>Shifting</td>
<td>Region2 (aft part)</td>
<td>( \alpha_3 )</td>
<td>[-0.02, 0.02 ]</td>
</tr>
<tr>
<td>7</td>
<td>Shifting</td>
<td>Region3</td>
<td>( \alpha_4 )</td>
<td>[-0.3, -0.2 ]</td>
</tr>
</tbody>
</table>

In this case, the hull form optimization problem is shown below:
\[ \min R_e = R_e(\text{Fr} = 0.3) \]
\[ x \in [0.515, 0.545] \]
\[ y \in [0.005, 0.021] \]
\[ z \in [-0.049, -0.0344] \]
\[ s.t. \ \alpha_1 \in [-0.02, 0.02] \]
\[ \alpha_2 \in [0.2, 0.3] \]
\[ \alpha_3 \in [-0.02, 0.02] \]
\[ \alpha_4 \in [-0.3, -0.2] \]  
(20)

Since the original deformation methods and ranges are set, the POD can be applied to do the design-space dimensionality reduction.

Before doing the POD, produced by Optimal Latin Hypercube Sampling (OLHS) method, a dense sampling is needed to obtain a series of new hulls (snapshots) to capture the hull form deformation that is regarded as a linear transformation. Here, \( N \) is set to be 1250, 2500, 5000, and 10000 respectively to see the change rule of POD result.

Through Eqs. 13–17, the eigenvalues can be got and the relationship between the energy ratio \( E_n \) and the dimensionality \( M \) through different numbers \( (N) \) of new sample hulls is given in Fig. 4.
Fig. 4 Geometric variance retained by a dimensionality-reduced space of different dimensionality $M$ and sample hulls’ sum $N$.

From the figure above, the dimensionality can be chosen as $M = 5$ to satisfy the energy ratio criteria. The bases of each mode calculated by different numbers ($N$) of new sample hulls are given by Fig. 5.

It should be stated that the label ranges $u_1, u_2, u_3$ in each mode represent $\max_{\lambda_i \times x} (x_i - \bar{x})^T u_j \max_{\lambda_i \times x} (x_i - \bar{x})^T u_j \max_{\lambda_i \times x} (x_i - \bar{x})^T u_j$ for relatively obvious scales. From Fig. 5, it can be easily seen that there seems to have a convergence trend of the bases when $N \geq 2500$. Therefore, the bases calculated by the 5000 new sample hulls are chosen to reconstruct any new (deformed) hull form, and the new design variables are shown in Table 3.

Table 3. Optimization design variables in dimensionality reduction case

<table>
<thead>
<tr>
<th>No.</th>
<th>Basis</th>
<th>Design Variables</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$u_1$</td>
<td>$a_1$</td>
<td>[-0.273,0.177]</td>
</tr>
<tr>
<td>2</td>
<td>$u_2$</td>
<td>$a_2$</td>
<td>[-0.120,0.111]</td>
</tr>
<tr>
<td>3</td>
<td>$u_3$</td>
<td>$a_3$</td>
<td>[-0.133,0.086]</td>
</tr>
<tr>
<td>4</td>
<td>$u_4$</td>
<td>$a_4$</td>
<td>[-0.073,0.073]</td>
</tr>
<tr>
<td>5</td>
<td>$u_5$</td>
<td>$a_5$</td>
<td>[-0.061,0.061]</td>
</tr>
</tbody>
</table>

The error of a deformed hull by original deformation methods and its corresponding reconstructed hull can be analyzed through a simple example. Fig. 6 shows the hull line comparison of the initial hull with a generated bulbous and a deformed hull controlled by 7 design variables.
Since we select $M = 5$, we can see what contribution each mode gives by setting $K$ from 1 to 5, and the reconstructed hulls are:

$$x^{rec}(K) = \bar{x} + \sum_{j=1}^{K} \alpha_j \mu_j$$  \hspace{1cm} (21)

After setting $K$ from 1 to 5, the reconstructed hulls compared with the original modified hull are shown below.

![Hull line comparison](image)

**Fig. 6 Hull line comparison of the initial and deformed hulls**

It can be inferred through Fig. 7 that with the increase of the dimensionality, the difference between the reconstructed hull and the real modified hull is becoming smaller.

Since we have ensured that the 5 modes can retain relatively whole deformation, the dimensionality of the design space is reduced from 7 to 5 (but not less than 5 cause the error is relatively large) and it can be reasonably predicted that the optimization result of the case with dimensionality 5 will be better than that of the case with dimensionality 1 or 3. Therefore, several optimization cases are set to prove it.

Before constructing Kriging surrogate models for different dimensionality $M$ (1, 3, and 5), 20, 60, and 100 sample points should be chosen by OLHS method.

Fig. 8 shows the comparison of the wave elevation calculated by NMShip-SJTU and naoe-FOAM-SJTU solvers. It is necessary to say that since the verification and validation of the naoe-FOAM-SJTU solver in the resistance calculation has already been given by Shen and Wan (2013), it’s not listed here. It can be seen that the amplitudes and the locations of the peaks and troughs of each wave system are almost the same, which can conclude that NMShip-SJTU solver can predict the wave elevation in calm water with relatively high fidelity.

Furthermore, experimental measurements given by the Ship Research Institute (SRI) and computational results by the NMShip-SJTU solver of the wave-making resistance coefficient $C_w$, the friction resistance coefficient $C_f$ given by ITTC 1957 formula, and the total resistance coefficient $C_t$ which is simplified as the sum of $C_w$ and $C_f$ are shown in Fig. 9.
It can be seen that the variation tendency between the experimental measurements and computational results with \( Fr \) increasing is almost the same, and the calculated total drag coefficient is quite close to the experimental values, which shows that NMShip-SJTU solver is effective and efficient to do the hull form resistance optimization especially for the ships sailing in relatively high speeds.

After doing the evaluations through NMShip-SJTU solver and the 1957 ITTC frictional coefficient formula, the total drag of the new sample hulls can be calculated to do the surrogate model construction and optimization. The optimization parameters are listed: population size 50, maximum generation 300, crossover fraction 0.8, and migration fraction 0.2.

What calls for special attention is that since the new \( M \) (1, 3, or 5) design variables’ ranges are determined by Eq. 19, it’s rough to some extent if there are mutual constraints among the new design variables. In fact, it’s usually difficult to obtain the constraints through theoretical analysis, but from a practical point of view, given by the traditional deformation methods controlled by 7 variables, a dense sampling of the new sample hulls can give the new design variables’ distribution, the projections of which can be used to get the constraints of the new samples. Fig. 10 shows the relationship (projection) among the new design variables through 5000 new sample hulls, where the blue points and the green points represent the 5000 dense samples and 100 samples in the case of \( M = 5 \) respectively.

Seen from Fig. 10 (b), (g), and (i), some linear constraints on the boundary of the dense samples should be given to limit the new design space:

\[
\begin{align*}
& f_1(a_1, a_2) \leq 0 \\
& f_2(a_1, a_3) \leq 0 \\
& f_3(a_1, a_4) \leq 0 \\
& f_4(a_1, a_5) \leq 0 \\
& f_5(a_2, a_3) \leq 0 \\
& f_6(a_3, a_4) \leq 0 \\
& f_7(a_4, a_5) \leq 0 \\
& f_8(a_5, a_1) \leq 0
\end{align*}
\]  

Therefore, the new optimization problems for \( K =1, 3, 5 \) can be given as:

\[
\begin{align*}
\text{min } R &= \frac{R_f}{Fr = 0.3} + \frac{R_c}{Fr = 0.3} \\
\text{s.t. } &
\begin{align*}
(K=1) &
\quad a_i \in [-0.273, 0.177] \\
(K=3) &
\quad a_i \in [-0.273, 0.177] \\
(K=5) &
\quad a_i \in [-0.273, 0.177]
\end{align*}
\]

Finally, we use genetic algorithm to get the optimization results of the certain cases above. The optimal hulls with their design variable values and total drags are shown in Tables 4-5. In this paper, names KLE-1, 3, 5 and Optimal represent the optimal hulls in case of \( M = 1, M = 3, M = 5 \) which have dimensionality reduction and 7 design variables with no dimensionality reduction respectively.
Table 4. Comparison of the optimal hulls’ design variable values

<table>
<thead>
<tr>
<th>Design Variables</th>
<th>KLE-1</th>
<th>KLE-3</th>
<th>KLE-5</th>
<th>Optimal (7 d. v.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_1/x$</td>
<td>0.1784</td>
<td>0.1470</td>
<td>0.1518</td>
<td>0.5290</td>
</tr>
<tr>
<td>$a_2/z$</td>
<td>-0.0958</td>
<td>-0.0818</td>
<td>-0.0375</td>
<td></td>
</tr>
<tr>
<td>$a_3/y$</td>
<td>0.0305</td>
<td>0.0273</td>
<td>0.0050</td>
<td></td>
</tr>
<tr>
<td>$a_4/a_1$</td>
<td></td>
<td>-0.0729</td>
<td>0.0200</td>
<td></td>
</tr>
<tr>
<td>$a_5/a_2$</td>
<td></td>
<td>-0.0010</td>
<td>0.2000</td>
<td></td>
</tr>
<tr>
<td>$a_6$</td>
<td></td>
<td></td>
<td>0.0200</td>
<td></td>
</tr>
<tr>
<td>$a_7$</td>
<td></td>
<td></td>
<td>-0.2000</td>
<td></td>
</tr>
</tbody>
</table>

Table 5. Comparison of the objective function value of initial and optimal hulls

<table>
<thead>
<tr>
<th>Hull</th>
<th>$R_t/N$</th>
<th>$R_t$ Decrease Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>20.52</td>
<td>-</td>
</tr>
<tr>
<td>KLE-1</td>
<td>18.75</td>
<td>8.60%</td>
</tr>
<tr>
<td>KLE-3</td>
<td>18.4</td>
<td>10.30%</td>
</tr>
<tr>
<td>KLE-5</td>
<td>18.2</td>
<td>11.30%</td>
</tr>
<tr>
<td>Optimal (7 d. v.)</td>
<td>17.65</td>
<td>14.00%</td>
</tr>
</tbody>
</table>

Fig. 11 Hull line comparisons of initial and optimal hulls

The hull line comparisons are shown in Fig. 11. Totally speaking, we can see from Fig. 11 that the optimal hulls change bigger when the dimensionality of the design space is larger, and the KLE-5 hull is closest to the Optimal hull. Furthermore, shown in Fig. 12, the free surface wave elevation comparisons are given through evaluations by NMSHIP-SJTU solver to have a deep analysis.

Fig. 12 Wave elevation comparisons of initial and optimal hulls by NMSHIP-SJTU (Unit: m)

It is obvious that the wave peaks and troughs of the optimal hulls decrease compared with those of the initial hull, and the KLE-5 optimal hull has the best optimized effect of the three design-space dimensionality-reduced optimization cases.
Fig. 13 Pressure distribution comparisons of initial and optimal hulls by NMShip-SJTU (Unit: Pa)

For further verification, the calm-water total drags of the initial and optimal hulls are predicted by naoe-FOAM-SJTU solver, and their free surface wave elevation comparisons evaluated by naoe-FOAM-SJTU can be seen in Fig. 14. Seen from Fig. 14, the peaks and troughs of bow and stern diverging waves reduce, and this decreasing trend is like that of the results given by NMShip-SJTU (shown in Fig. 12). This not only ensure the reliability of the optimal hulls, but also indicate that the NMShip-SJTU solver can predict the wave-making resistance (or the wave elevation) in calm water with relatively high fidelity and efficiency.
The pressure distribution comparisons calculated by naoe-FOAM-SJTU are given in Fig. 15, showing a similar varying trend of the optimal hulls, and the KLE-5 optimal hull also has the best optimized effect of the three design-space dimensionality reduced optimization cases.

CONCLUSIONS

Through Proper Orthogonal Decomposition, the dimensionality of the design space of the hull form optimization problem can be reduced, which saves the computational time and resource of the new sample hulls, especially for simulation-based hydrodynamic performance optimizations. Specific mathematical expressions of the method used for hull form deformation are given to be a proof and practical guide. At the same time, the choosing rule of sum of dense sampling points and the reduced dimensionality is given, and the method of obtaining constraints among the new design variables are also mentioned. Furthermore, compared with the optimal hull with no dimensionality reduction, the optimal hull after dimensionality reduction has a relatively good effect, which is vital for future comprehensive hydrodynamic performance optimization problems, since it can greatly reduce the amount of calculation and improve the efficiency of optimization at the same time. Therefore, the design-space dimensionality reduction method has great potential in terms of ship hydrodynamic performance optimization.

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REFERENCES


