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Multiobjective Optimization for Ship Hull Form Design Using SBD Technique

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Abstract: With the rapid development of computer technology and the continuous improvement of optimization theory, optimization techniques have been introduced into the field of ship design. Optimization algorithms and advanced CFD techniques are successfully integrated together into what is known as Simulation-Based Design (SBD) techniques, which opens a new situation for hull-form optimization design and configuration innovation. In this paper, fundamental elements of the SBD techniques are described and crucial components are analyzed profoundly. Focus is on breaking through key technologies as hull geometry modification and reconstruction, global optimization algorithms, and codes integration. Combined with high-fidelity CFD codes (on RANS), an automatic hull-form design optimization framework is established. Based on that, an application of the framework application for a surface combatant hull multi-objective optimization is illustrated. The results show that the reduction of the total resistance is about 6% for the optimized hullform at the design speed (F_n=0.28). The given combatant design optimization example demonstrates the practicability and superiority of the developed SBD framework for the mid-high speed ship.

Keywords: hull form, CFD, optimization, design, SBD framework

1 Introduction

For a long time, Computational fluid dynamics (CFD) technique has been received great attention in the field of ship hydrodynamics, which are the fastest progress hydrodynamics emerging trends in the past twenty years. However, it main applied to evaluation and prediction of ship performance. Hullform design is still adopted the traditional method based on experience and model test database, and innovative methods rare; which is difficult to obtain the optimal design for the ship hydrodynamic performance. Many researchers and design engineers still employ the terminology optimization when what they mean in practice is that after starting

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from a non-satisfactory configuration, they have tries two or three other ones and chosen at the end best one. This is undoubtedly related to optimization.

Today, CFD technology rapid development provides an accurate and reliable tool to the ship hydrodynamic performance evaluation and prediction; the rapid development of multi-disciplinary and multi-objective optimization technique provides a scientific method to solve complex engineering optimization design problems. Accordingly, the implementation of "hullform optimization design", obtaining the optimal hullform becomes possible in given constraint and objective.

Along with the development of CFD technique, CAD technique and optimization technique, a new hullform design optimization technique, namely Simulation-Based Design technique appeared. It is different from the traditional "optimization" (select the best case in other alternatives), but applied the optimization technique to obtain the minimized objective function under given constraints condition, meanwhile, and utilized CFD tool to compute the flow field and evaluate the objective function.

To develop Simulation-Based Design techniques for shape design, four main components must be built and are common among many different applications (see Figure1). First, an optimization technique that can be used to minimize the objective functions under given constraints. Second, a hull geometry modeling and modification technique that provides the necessary link between the design variables (and they variations) and the deformation of the body shape. And third, a CFD solver used as analysis and evaluation tools to return the value of the objective function and of functional constraints. Finally, hull-form optimization design framework needs to be set up by integrating the above three components, and automatic optimization process needs to be realized.

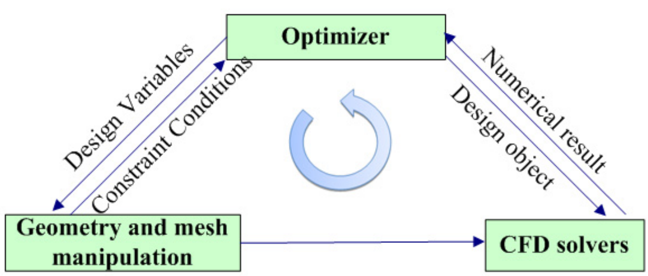


Figure 1: SBD-based hullform design optimization environment

In recent years, the SBD technique is used for hullform design, applications of CFD tools to hydrodynamic optimization (mostly for reducing calm-water resistance and wave patterns) have been reported in a significant number of studies. These studies attest to a rapidly growing interest in hydrodynamic optimization [Day (2000), Peri (2001, 2003), Tahara (2004, 2006), Pinto (2007), Kim (2008), Campana (2009), Diez (2010), Yang (2010), Han (2012)].

The CFD solvers used in these studies consists of RANS solver or potential flow solver with various approximations to analyze ship hull boundary surface, free surface, and flow domain. Using an analysis tool based on potential flow, Day and Doctors [Day (2000)] introduced a genetic algorithm to solve a global optimization problem. Numerical shape optimization of a tanker ship hull has been carried out by Peri et al. [Peri (2001)]. During the process, the total resistance is usually computed via a CFD solver based on a linear potential formulation of the steady free-surface flow past a ship. The bow bulb redesign was undertaken by Newman et al. [Newman (2002)] using sensitivity analysis and complex variable finite difference approach. The method used a RANS solver to minimize sonar dome vortices neglecting free surface effects. An application to stern, sonar dome, and bow form of naval combatants was considered by Tahara et al. [Tahara (2004)] using RANS. In addition, Tahara et al. [Tahara (2006)] used a RANS solver for self-propulsion simulator to consider thrust deduction and maneuverability.

Several optimizations based on deterministic or probabilistic algorithms have been applied for ship hull form optimization. Early attempts to adopt this efficient, gradient based optimizations technique in ship hydrodynamic optimizations reported in Valorani et al. [Valorani (2003)]. A SQP method was employed to optimize the DTMB Model-5415 in Tahara et al. [Tahara (2004)]. A GO algorithm for multi-objective problems has been developed by Peri et al. [Peri (2003)] for both a commercial container ship and a destroyer ship. Pinto et al. [Pinto (2007)] solved a shape optimization of a container ship using deterministic particle swarm optimization algorithm. The amplitude operator on peaks of heave and pitch motion response of the ship advancing at fixed speed in head seas was reduced.

A number of alternative hull geometry modeling techniques have been developed. Kim [Kim (2008)] has developed the approach based on parametric hull representation by introducing a modification function as well as bell-shape modification function. Valorani et al. [Valorani (2000)] applied a surface patch to the bulbous bow geometry which was modified by relocating control points; the constraints consisted of a limited range of motion for the control point. Campana et al. [Campana (2009)] utilize Free-Form Deformation approach to modify complex hull geometries such as bulbous bow or full hull form in ship hydrodynamics performance optimization. A combined local and global hull form modification approach is developed by Kim and Yang et al. [Kim (2010)] and integrated into a CFD-based practical hydrodynamic optimization tool. This optimization tool has been applied to the hydrodynamic design of the Series-60(Cb = 0.6) hull for reduced drag.

In addition, many interesting works are presented by Campana and colleagues. The key technologies of SBD as hull geometry modification and reconstruction, global optimization algorithms, parallel computing and approximation management approach are studied profoundly. In a series of papers, Peri and Campana [Peri (2001)] investigated a variable-fidelity approach to speed up the optimization process using free surface RANS in single- and multi-objective problems, while Peri and Campana [Peri (2003)] developed a global optimization algorithm, applied to the solution of the same test, and the experimental campaign carried out to assess the success of the optimization. More recently, Peri et al. [Peri (2010)] and Campana et al. [Campana (2009)] summarized the previous developments and demonstrations of the SBD tool box in dealing with complex design problems. And then the SBD framework is applied to the optimization of a catamaran propelled by waterjets [Peri (2012)].

Diez et al. [Diez (2010)] presents a formulation for multidisciplinary robust design optimization of vessels, subject to uncertain operating conditions. The formulation couples the multidisciplinary design analysis with the Bayesian approach to decision problems affected by uncertainty.

Numerical shape optimization of a container ship and LPG carrier has been carried out by Han et al. [Han (2012)] employing parametric curves generated by fairness-optimized B-Spline form parameter curves, labeled as F-Spline. The optimal ship with a completely different bulb shape was successfully validated by model experiment, showing a 5.7% improvement in total resistance and a 7.8% improvement in delivery power.

These papers cited above witness that the SBD techniques (CFD-based hullform design) are receiving growing consideration in the ship hydrodynamics design field. They paper will describe some algorithms and methods for the numerical optimization of a ship's calm-water resistance performance, for either local or global optimization problems.

In this paper, firstly, focus is on breaking through key technologies as hull geometry modification and reconstruction, global optimization algorithms, and codes integration. Based on that, combined with high-fidelity CFD codes (on RANS), an automatic hull-form design optimization framework is established. And then, in order to demonstrate the practicability of the SBD framework, multi-objective optimization design of a mid-high speed ship at three different speeds is illustrated. The succession of design optimization confirms the applicability of the developed SBD framework to the ship design problems.

2 Global optimization algorithms

Optimization technique is used for exploring the hullform design space and obtaining the optimal solution of optimization problem. Therefore, selecting what kinds of optimization algorithms, so that it can quickly and accurately search the optimal solution in the design space, is one of the research focuses for hull optimization design.

The traditional gradient-based optimization algorithms are widely applied, mainly due to their good convergence properties and computational efficiency when a relatively small number of variables are considered. However, due to nonlinear constraints, non-convex feasible design spaces are quite common in practical problems as well as multimodality of the objective functions, the local optimization algorithms might be trapped in the local minima and be inefficient in solving these problems. With the increase of computer power and the development of efficient global optimization algorithms, in recent years non-gradient-based algorithms have attracted much attention [Li (2011), Santos (2012)]. Global optimization algorithms provide several advantages over local optimization algorithms. They are generally easy to program and to parallelize, do not require continuity in the problem definition, and are generally better suited for finding a global, or near global, solution. Accordingly, the author suggests that the global optimization algorithms should be chosen in solving practical engineering optimization problems.

There are so many different types of GO algorithms exit, for an extensive coverage of various methods of GO useful references are Törn [Törn (1989)] and Liu [Liu (2012)]. A Particle Swarm Optimization (PSO) algorithm which was introduced by Kennedy and Eberhart [Kennedy (1995)] for the first time is adopted in this paper. Since the PSO algorithm was originally introduced, it soon developed into a powerful global optimization method, and it has been successfully applied to large-scale problems in several engineering disciplines [Eberhart (2001), Venter (2004), and Pinto (2004)]. This section will introduce standard PSO algorithm (SPSO) procedures and its improvement.

2.1 Standard PSO algorithm

The PSO algorithm assumed that each individual in the particles swarm is composed of three D-dimensional vectors, where D is the dimensionality of the search space. These are the current position$\vec{x}_i$, the previous best position$\vec{p}_i$, and the velocity$\vec{v}_i$. A particle swarm is composed of m number of particles, the position of the number i particle expressed as $\vec{x}_i = [x_{i_1}, x_{i_2}, \cdots x_{i_D}]$, and so the velocity is $\vec{v}_i = [v_{i_1}, v_{i_2}, \cdots v_{i_D}]$, the best position find by the number i particle is$\vec{p}_i = [p_{i_1}, p_{i_2}, \cdots p_{i_D}]$, the best position find by the whole particles expressed as $\vec{p}_g = [p_{g_1}, p_{g_2}, \cdots p_{g_D}]$, then use the following formulation to update the velocity and position:

$$\vec{v}_i(n+1) = \vec{v}_i(n) + c_1 r_1(\vec{p}_i - \vec{x}_i(n)) + c_2 r_2(\vec{p}_g - \vec{x}_g(n)) \quad (1)$$

$$\vec{x}_i(n+1) = \vec{x}_i(n) + \vec{v}_i(n) \quad (2)$$

Where, i=1,2,...m represent different particles, $c_1$and c_2 (called study factors or acceleration coefficient) are positive constants, which adjust the flying step between the best positions which found by themselves and by their neighbors. In general, $c_1 = c_2$=2; $r_1$and $r_2$are random numbers equally distributed between 0 and 1, p_i is the best position found by particle i, and p_g is the best position found by the swarm up to iteration n, n is the iteration time. The v_i is confined to the region [-v_{max}, v_{max}] to prevent the particles moving too quickly to lose the best solution, and the v_{max} is determined according to the problem. When the velocity is small enough or reach the maximum iteration time defined in the beginning, the algorithm will stop and output the best solution.

The basic PSO algorithm is composed of the following six steps:

Step 1: Initialize a population array of particles with random positions and velocities in D-dimensions in the search space;

Step 2: For each particle, evaluate the desired optimization fitness function in D variables. Store the best position p_i and fitness of every particles, then select particle's position whose fitness is best among the whole particles as the particle swarm' best position p_g;

Step 3: Calculate the velocity and position of the particle for the next step according to the Eq.1 and Eq.2;

Step 4: Compute the fitness of each renewed particles and evaluation with it'sp_i, if new value is better thanp_i, then set the current location to the particlesp_i;

Step 5: Compare each particle's fitness evaluation withp_g, if current value is better thanp_g, then set the current value top_g;

Step 6: If the pre-define criterion is met (usually a sufficiently good fitness or a maximum number of iterations), then exit iteration and output the optimal solution; other arise, then go back to step 3.

The basic PSO described above has a small number of parameters that need to be fixed. One parameter is the size of the population. This is often set empirically based on the dimensionality and perceived difficulty of a problem. Motivated by the desire to better control, the scopes of the search reduces the importance ofv_{max}, and perhaps eliminate it altogether, the following standard PSO algorithm was proposed:

$$\vec{v}_i(n+1) = w\vec{v}_i(n) + c_1 r_1(\vec{p}_i - \vec{x}_i(n)) + c_2 r_2(\vec{p}_g - \vec{x}_g(n)) \quad (3)$$

Where w was named the "inertia weight", it regulates the trade-off between the global and local exploration abilities of the swarm. Thus select an appropriate value could reduce the number of iterative and improve solve speed. At the beginning, the value of w was set to a constant value [Shi (1998)], but subsequent experiment indicated that dynamic value could get better optimal results. A large inertia weight facilitates global exploration, while a small one facilitates local exploration, regulated the value of w could trade-off convergence speed and local search abilities. At present, the linearly decreasing weight (LDW) strategy introduced by Shi [Shi (1998)] is widely adopted. It was called the standard PSO algorithm.

$$w = w_{\max} - n\frac{w_{\max} - w_{\min}}{n_{\max}} \tag{4}$$

Where $w_{\max}$represent the large inertia weight and $w_{\min}$ represent the lower one, n is the number of iterative and $n_{\max}$ is the total number of iterations. The value of w normally chosen between 0.1 and 0.9, it would be reduced to a lower value corresponds to the iterative. In the adaptation of w using a fuzzy system was reported to significantly improve PSO performance. Nonetheless, due to the particle to own history best position and group history best position gathered, leading to the particle population fast convergence effect, the standard PSO algorithm is easy to appear the trapped into local minima, premature convergence and stagnation phenomenon. At the same time, the performance of the PSO algorithm also depends on the algorithm parameters. In order to overcome the shortages, the researchers have put forward various improvement measures, such as: population initialization, parameter selection, neighborhood topology, variant specialization, hybrid and adaptive particle swarms, etc.

2.2 *Improved of the standard PSO algorithm*

In this paper, the population initialization and the algorithm parameters are selected for improving the performance of the standard particle swarm optimization algorithm, respectively.

2.2.1 *Population initialization based on DOE*

Random method is used to initialize the particle's velocity and position in the standard particle swarm optimization algorithm. This method could make the population can't even cover the whole design space.

In this paper, the Design of Experiment method (orthogonal design method) is adopted for initializing particle's velocity and position. The initialization method can more fully explore design space with less population size.

2.2.2 Adaptive inertia weight

With the increase of the update generation, inertia weight gradually decline in the standard particle swarm optimization algorithm. In the later stage, the SPSO algorithm will lose the ability to explore new areas because the inertia weight is too small. This paper uses adaptive inertia weight method. The inertia weight will be automatically changed according to the individual adaptive value and group average adaptive value in the iteration process. The expression is as follows:

$$w = \begin{cases} w_{\min} - \frac{(w_{\max}-w_{\min})(f-f_{\min})}{(\bar{f}-f_{\min})} + n^2 \frac{(w_{\max}-w_{\min})}{n_{\max}^2} & f \leq \bar{f} \\ w_{\max} & f > \bar{f} \end{cases} \tag{5}$$

Where f is the current adaptive value. $\bar{f}$ and $f_{\min}$ is the average and the minimum adaptive value of current all particles, respectively. When the adaptive value of the group each particle tend to be consistent, inertia weight will increase, while will be able to prevent entraping local optimization; When the adaptive value of each particle is dispersed, inertia weight will decrease, which will benefit particles tend to the optimal place. Adaptive inertia weight method is advantageous to increase the convergence speed and avoid the premature, and can effectively improve the global and local search ability.

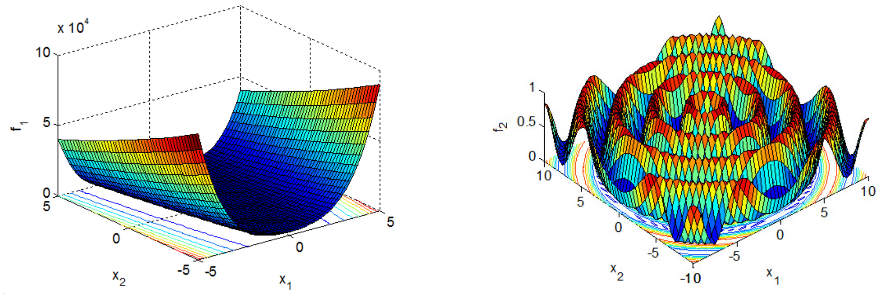
2.3 Test of IPSO algorithm

In order to validate the performance of the improved algorithm, two benchmark functions are selected for testing the performance of IPSO algorithm and SPSO algorithm. Two function as follows:

$$f_1(x) = \sum_{i=1}^{D-1} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2) \tag{6}$$

$$f_2(x) = 0.5 + \frac{\sin^2(\sqrt{\sum_{i=1}^{D} x_i^2}) - 0.5}{(1.0 + 0.001(\sum_{i=1}^{D} x_i^2))^2} \tag{7}$$

Where D is the dimension number. $f_1(x)$ is a unimodal function and is called Rosenbrock function, its variables has a strong coupling each other. The global minimum of the function is 0, when x^* = (1, 1,..., 1). $f_2(x)$ is a multimodal function and is called Schaffer function, its global minimum value is 0, when x^* = (0, 0,..., 0). Two dimensional forms of two benchmark functions are shown in Figure 2.



(a) Rosenbrock function (b) Schaffer function

Figure 2: Benchmark test functions (two dimension)

The same parameter is selected for IPSO and SPSO algorithm in the test process, see Table 1. Orthogonal design method is used to initialize IPSO algorithm. Each function is solving twenty times, optimization results take its mean value.

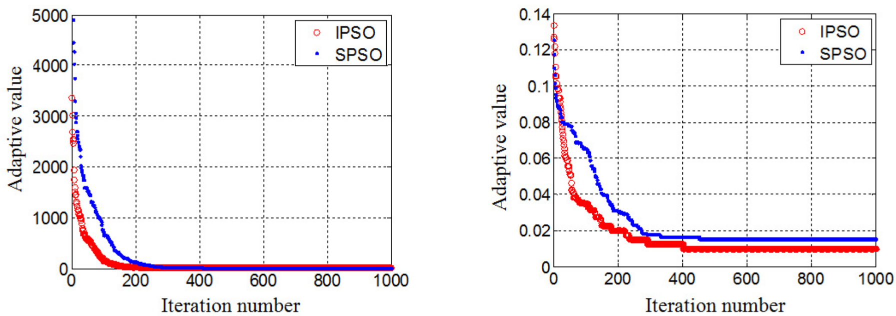
Table 1: Parameters of optimization algorithm

Cognitive parameterC_1	2.0	Social parameter C_2	2.0
Inertia weight value W_{max}	0.9	Inertia weight valueW_{min}	0.3
Particle dimension D	10	Particle size M	20

Table 2: The average fitness of test function

Test function	Generation number N	x_i		Optimal solution	
		min	*max*	SPSO	IPSO
f_1	1000	-5	5	11.924	4.855
f_2	1000	-10	10	0.0152	0.0097

The optimization results of two benchmark functions is shown in Table 2, it shows that the IPSO algorithm are better than SPSO algorithm. The optimization iterative process curve of two benchmark functions are shown in Figure 3, the convergence speed and accuracy of IPSO algorithm is faster and higher than SPSO algorithm. Test results show that the IPSO algorithm has stronger overcome precocious ability and faster convergence speed than SPSO algorithm.



(a) Rosenbrock function (b) Schaffer function

Figure 3: Iterative process curve of test function

2.4 MOPSO algorithm

In this study, the IPSO algorithm presented has been extended to deal with multi-objective problems. The swarm particles, which move themselves in the design space, are driven by a combination between the personal best position for each particle and the overall best position among all the particles, with a velocity given by Eq.(3). In order to apply this algorithm to multi-objective problems, the concept of "best position" is replaced by the concept of closest Pareto point.

Each Pareto optimal solution is defined as a possible new P_b, i.e., a guide, and the swarm is subdivided into l smaller swarms, all capable of in dependent evolution, each swarm following its own guide. By defining different guides for the sub-swarms it is possible to build a wider Pareto front. The strategy adopted to assign the particles to the guides (i.e. to form the sub-swarms) is based on the distance in the design space between the particles and the Pareto solutions (details are given in Pinto (2007) and ShengZhong (2012)).

Step I. (Distance evaluation) the ith particle evaluates its distance, in the design variables space, from the Pareto optimal points;

Step II. (Guide selection) the ith particle selects its closest Pareto optimal point as a guide. Set $i = i+1$ and go to Step I until $i = N_p$ (N_p is the numbers of Pareto optimal solution)

As a consequence, the global best position is replaced with the closest Pareto point coming from the Pareto front obtained by considering all the evaluations by all the particles, and the personal best position is now the closest Pareto point among those of the Pareto front. The equation for the computation of the velocity is the same, but the meaning of the two attractors has changed.

3 Hull geometry modification and reconstruction

An accurate and effective hull geometry modeling and modification technique plays an important role in the CFD-based hullform design optimization. Flexibility of the geometry modeling and modification technique may greatly affect the freedom of an optimizer to explore the design space. Specifically, it needs to ensure several aspects. First of all, only a small number of parameters, i.e., design variables, are required for the hull geometry variation to minimize the number of objective function evaluations. Second, large variation of hull forms can be obtained to allow for sufficient free-form design, i.e., to produce different type of hullform. Third, modified portion can join the original design smoothly without discontinuities when only a part of the hull needs to be optimized. Finally, practical hullform can be preserved and various geometrical constraints can be easily implemented in the optimization process.

At present, the hull geometry modification and reconstruction approach includes a lot of kinds , such as classical Lackenby approach, morphing approach, parametric model approach, Bezier Patch approach, Free-Form Deformation approach and CAD - based approach, etc. Bezier Patch and FFD approach are suitable for hull local geometry reconstruction and integral geometry reconstruction, respectively. They have very good adaptability, has been widely used in ship form optimization design [Peri (2003)]. The developed SBD framework includes the above two methods. Bezier Patch has been used for the bulb geometry modification and reconstruction [Shengzhong (2012)]. In this paper, FFD approach is adopted to modify the hull geometry.

FFD approach, developed by Sederberg and Parry in the field of computer graphics, is a very flexible approach to deform a 3D object, whose geometry is given by points. This approach can be essentially reduced to a 4D-Bezier patch to be applied to the hull surface. If we now define a box surrounding the hull surface, we can define a Bezier polynomial inside this 3D domain, producing a scalar function of the 3D space. This function, defined as

$$X(s,t,u) = \sum_{i=0}^{l}\sum_{j=0}^{m}\sum_{k=0}^{n} B_{i,l}(s)B_{j,m}(t)B_{k,n}(u)Q_{i,j,k} \tag{8}$$

Where *X(s,t,u)* are the coordinates of the ship surface $Q_{i,j,k}$ are the vectors of the control points in the $s-t-$ and $u-$ directions. $B_{i,l}$ $B_{j,m}$ and $B_{k,n}$ are normalized Bernstein basis functions of degree lm and $n$in the $s-t$ and u directions, respectively.

After constructing mapping relationship between the deformation object and the control points of the box, the modification and reconstruction of the object can be realized by moving the control point's position along the given direction. The control points of the box are assumed as design variables of the optimization problem. Above mentioned requirements can be easily satisfied. About FFD approach, some further developments are described, as well as the original approach, in Campana [Campana (2009)]

4 CFD solvers and integration framework

4.1 Evaluations of the objective function

CFD solvers used as analysis and evaluation tools to return the values of the objective function and functional constraints. The accuracy of CFD solvers has a large impact on the practical implementation and often also on the success of the optimization process. Generally speaking, before the design optimization is carried out, the validation and verification of CFD solvers should be first performed. At the same time, the improvement obtained by design optimization should larger than the numerical noise of CFD solvers.

The CFD solvers used in hullform design optimization studies consist of RANS solvers or potential flow solvers. Potential flow solver is very highly efficient in evaluating the objective function, but its accuracy is very poor. On the contrary, RANS solvers is very good accuracy, but its efficiency is low. How to guarantee the accuracy of the objective function solved, and meanwhile improve CFD solver efficiency, is the emphasis of shape optimization design research currently.

For an advanced fluid dynamic redesign of some part of an existing shape, accurate analysis tools are necessary for guiding the optimizer toward improved solutions. This is true also for ship redesign and the most advanced analysis tools available today to design engineers are RANS solvers. The degree of reliability of free-surface RANS code has constantly matured during the last 10 years.

In this paper, High Fidelity CFD tool adopted solves RANS equations for unsteady, three-dimensional incompressible flow by using the higher-order upwind difference method, the discrete formulation by a finite volume technique. And the free-surface is captured by adopting VOF method. The k-omega turbulence model is used to close of equations. The grids are multi-block-structured with hexahedral elements [Feng, (2005)].

The basic principle of meshing as follows: along the hull longitudinal, the grid of ship model bow and stern is properly dense, the central grid is relatively sparse; and the grid is also appropriate dense near free surface

With regard to grid manipulation, once the hull geometry is modified, the volume grid is adjusted accordingly. In this paper, for the different hulls geometric surface, the grid total numbers and topology structure can be assure consistency, the first layer grid dimension of hull surface is the same. That will be able to avoid the numerical error caused by meshing format. Hull geometry automatic modeling and mesh regeneration are realized by the GAMBIT software using its command flow.

4.2 Integration of hullform design optimization framework

Integration of the framework includes two contents; one is process integration of many modules, which solves some problems as modules (CFD tools, CAD tools and Optimization algorithm) interface one another, data transmission and exchange, the realization of automation process, etc. Another is the high performance parallel computing method, which solves some problems like the memory allocation and management of high performance computer, the optimization algorithm parallel. Its purpose is to improve the computational speed and save computational costs. The two contents are described as follow.

4.2.1 Process integration

The Process integration is to put each independent process unit connected together through effective data exchange interface, and according to the whole system run order operation to form a complete process integration platform. The process integration of automatic design optimization framework is described in Figure 4. It mainly contains four modules in the following.

a) Geometric parametric expression and reconstruction module (REFORM.EXE): This module function is the first parametric expression original hullform case, and then using some parameters (variables) to realize the ship shape automatic reconstruction. This input of module is the original hullform and design parameters (variables), output is hullform restructured.

b) Grid regeneration module (REMESH.EXE): this module function is to numerical modeling for input hullform, namely, to realize the automatic mesh generation for simulation domain. This module input is hullform, the output is the mesh file for the CFD numerical computation.

c) Ship hydrodynamic performance evaluation module (CFD.EXE): this module main function is to evaluate the ship hydrodynamic performance and calculate the objective function and constraint conditions. The module input is the mesh file, and the output is the value of objective function and constraint function.

d) Optimization strategy module (OPTIMIZOR.EXE): the module function is to explore hullform design space using optimization technique. It mainly includes DOE, response surface model, IPSO algorithm parallel manage method of CFD solvers and optimization algorithm, etc. This module input is the objective function value. In optimization process, output is design variables. Final output is the optimal objective function value and the corresponding design variables.

Ship hydrodynamic automatic design optimization framework is established by integrated the above four modules.

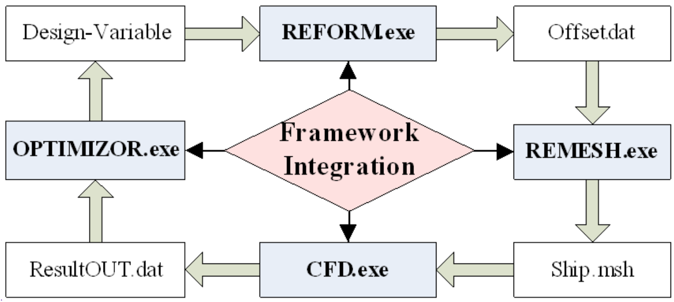


Figure 4: The process integration of automatic design optimization framework

4.2.2 *High performance parallel computing method*

A drawback of algorithm in evolutionary family, i.e., increase in computational load, is overcome by introducing parallel computing technique, i.e., Message Passing Interface (MPI) protocol.

For CFD-based optimization n+1 is number of population, and m is number of processors used for each CFD execution. When PSO was originally proposed, it was already recognized that there is a parallel nature of the algorithm along with the inherent efficiency if parallel processing. Nevertheless, relatively little work has been done in mapping PSO to existing and advanced parallel computing environments.

In the present study, a process is assigned to a processor so as to maximize CPU performance. Fig5 illustrates the present approach. Processor 0 is assigned to master the overall process; processors assigned to groups G-0 through G-n (when n+1 is number of populations), simultaneously execute the CFD method in parallel computational mode. In this scheme, total number of processors used for each CFD execution. This present parallel coding is based on Message Passing Interface (MPI) architecture, which is considered a suitable protocol for the present, distributed-memory-model parallel environment. The master and slave processes execute the same code, and each role is defined in a different subroutine. Fig 5 also shows an example for the main routine. Each calculation can be run in a parallel computational mode by using an assigned MPI group communicator and m processors. When the slave routines are called, the salve modes assigned to each group execute the calculation and send a signal to the master node when the calculation is

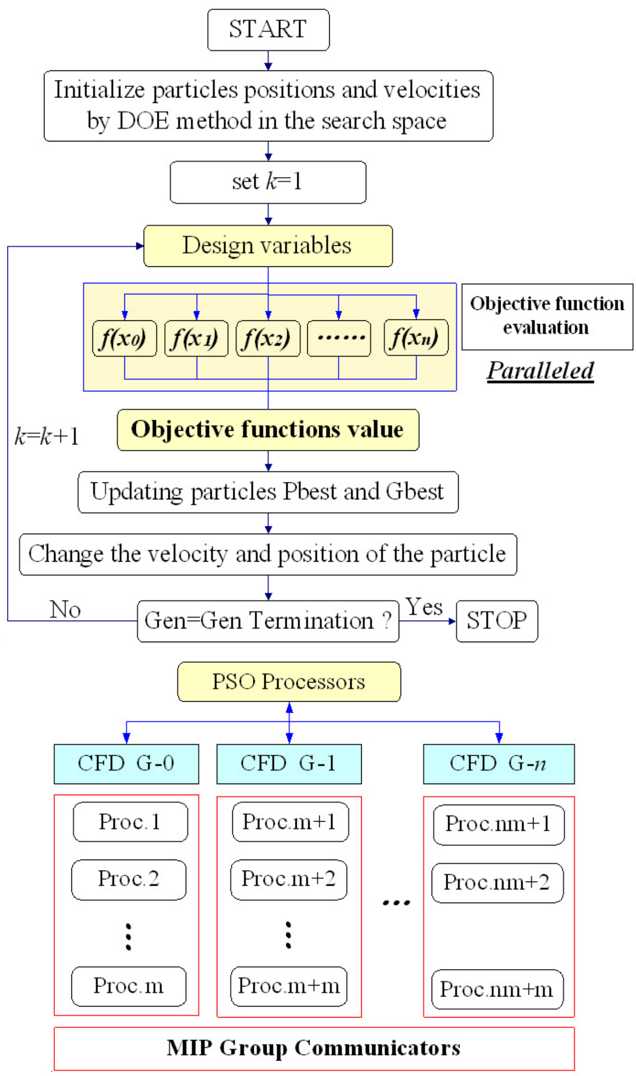


Figure 5: High-performance parallel-computing architecture and coding for multi-process algorithm

complete. The present coding method results in a considerably simplified message transmission as well as in a clear description of separate roles for master and slave nodes.

5 Applications for the mid-high speed ship optimization

For mid-high speed ship, the wave resistance is very large at the ratio of total resistance because of its high speed. And that wave resistance is very sensitive to ship shape change, if the hullform is properly modified, it is possible to significantly reduce the wave resistance, and obviously the total resistance is also greatly reduced. Therefore, the mid-high speed ship became the main research object for ship design based SBD techniques.

The surface combatant ship DTMB5415 configuration optimization design is one of the most representatives. The researchers choose the ship as the research object, have carried out much key technology research as optimization technique, geometry reconstruction technology, simple strategies, etc. and achieved gratifying results. To explore the practicability and superiority of the proposed hullform design framework in mid-high speed ship optimization problems, the well-known surface combatant ship DTMB5415 has been selected as a test case. The modifiable region is only the foremost part of the ship, i.e., the bow and the bulb (see Figure 6).

5.1 Definition of the Problem

The authors have demonstrated in their previous work [Sheng-Zhong (2012)] that the single design speed optimization can result in a hull form that has a large resistance reduction at the design speed. On the one hand the optimal hull form obtained for a given speed may not have a consistent resistance reduction in the entire speed range. It may have a large resistance increase at other off-design speeds. On the other hand, for mid-high speed ship, the influence of hullform change on the resistance is closely linked with speed. In different speed range, the influence of the same hullform change is different, and even has very big difference It is particularly obvious to the mid-high speed ships that utilize favorable wave interference by the bulb produced to reduce wave resistance. Thus, the present study is focused on the hydrodynamic optimization for a given speed range only, i.e., to develop optimal hull forms with minimum total resistance at the given design speeds (F_n=0.17 0.28, 0.37). Three objective functions are defined as follows:

$$\begin{cases} F_1 = R_{ti}^1/R_{t0}^1 & at \quad F_n = 0.17 \\ F_2 = R_{ti}^2/R_{t0}^2 & at \quad F_n = 0.28 \\ F_3 = R_{ti}^3/R_{t0}^3 & at \quad F_n = 0.37 \end{cases} \tag{9}$$

WhereR_{t0}^1andR_{ti}^1 denote the total resistance evaluated for the original hull form and intermediate hull form obtained during the optimization process, respectively.

Figure 6: Side view of the DTMB No. 5415

5.1.1 Modification of hull geometry

In the multi-objective optimization design for three different speeds, FFD approach is used for the bulb geometry reconstruction. The whole bulb area is normalized, and then it is put in a cube with 64 control points (see Figure7). Five group control points are chosen as five design variables. In each group, some points are grouped together, resulting into 1 variable. The first and second groups control points moved along y-coordination, to control the bow x-direction variations; the third and fourth groups control points moved along y-coordination, to control the bow y-direction variations; the fifth groups control points moved along z-coordination, to control the bow z-direction variations.

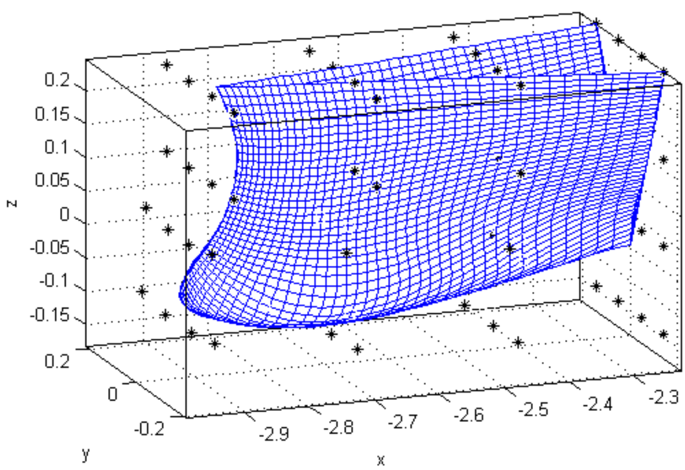


Figure 7: The bulb reconstruction using FFD approach

5.1.2 Validation of CFD solvers

Before the design optimization is carried out, the validation study is first performed for the original hullform DTMB 5415. Table 3. shows the comparisons of experimental measurements [details in Lei (2008)] and numerical predictions for the total resistance coefficients at the different speed, where the total resistance coefficients are obtained using the RANS approach. It can be seen from Table 3. that the total resistance coefficients are in consistent agreement with the experimental measurements (Bias errors within 3%). Table 3. also suggests that the CFD tool can predict the total resistance with reasonable accuracy. Therefore, the CFD tool based on the RANS approach is well suited for the hydrodynamic optimization of the hullform.

Table 3: Computational and experimental results of the total resistance coefficients for the original hullform

Fr	V(m/s)	$Re(10^6)$	C_T (10^{-3}) Cal.	C_T (10^{-3}) Exp.	E (%)
0.15	1.124	6.41	3.867	3.933	-1.7
0.17	1.273	7.25	3.901	3.937	-1.0
0.21	1.573	8.96	3.855	3.945	-2.3
0.23	1.873	10.67	3.962	4.049	-2.1
0.28	2.097	11.95	4.125	4.207	-1.9
0.33	2.472	14.09	4.436	4.563	-2.8
0.37	2.772	15.80	4.874	5.141	-5.2

5.1.3 Approximation strategy

In order to search for the hull forms that have possible resistance reduction at three design speeds, it is necessary to employ the multi-objective optimization algorithms. In this study, MOPSO algorithm has been extended to provide a set of optimal solutions using the Pareto front technique.

The maximum number of iterations (i.e., generations) and populations (i.e., swarm) is set as 20 and 40 respectively, which approximately yields a total of 20*40M evaluations of the objective functions in each case, where M is the number of the objective functions used in each case (M = 3 in the present study). It should be noted that the multi-objective PSO algorithms require a large number of objective function (flow) evaluations. In order to reduce the computational cost, the approximation strategy based on experimental design and response surface model is adopted.

Firstly, the design problem is analyzed through Design of Experiment method. Secondly, the Response Surface Model is established to use the results of DOE, and then Pareto optimal solutions are obtained to solve the RSM by MOPSO algorithm. Finally, the results are validated by high-fidelity CFD tool. The Approximation strategy and procedure are shown in Figure 8.

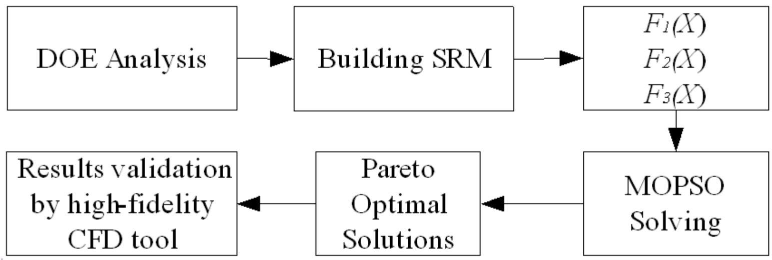


Figure 8: The procedure of multi-speed optimization

5.2 Design optimization results

Multi-objective optimization results show that three objective functions are basically the same convergent tendency (see Figure 9). Pareto front shape almost appears as a bit, and the optimal solution set only contains two optimal solutions Opt1 and Opt2. The income of total resistance and the corresponding design variables for the two optimal solutions are almost the same at three different speeds. Therefore, this paper only analyzes the opt1 result.

The comparison of shape between Opt1 and the original is shown in Figure 10, which clearly display some common geometrical trends.

1) The relevant difference is the extension of the bulb in the forward (x) direction;

2) A reduction of the maximum width (y) of the bulb is reduced by about 10%;

3) A trend to uplift of the bulb in the upward (z) direction;

4) In addition, a very slight change of the wetted surface area and the displacement are -0.6% and -0.4%, respectively.

The numerical results for the objective function show that the SBD techniques are able to identify improved designs with lower total resistance with respect to the original Model 5415. Comparisons of the resistance components between the original and optimized hullforms at the different speeds are shown in Table 4. The residual resistance reductions are obtained over the entire speed range. The maximum reductions in terms of the residual resistance are 20.82%. The variation in wetted surface area and volume are less than 0.5%. The total resistance reduction could be larger in the full scale case.

Reductions of the total resistance with respect to the original hull are also reported in Figure 11 as a function of the Froude number (values below 0% represent improved performance). The results show that the reduction of total resistance is about 3.80%, 5.98%, 4.70% for the optimized hullform at the three different speeds (F_n=0.17, 0.28, 0.37), respectively. It may be of interest to look at off-design conditions too: in the entire speed range, a maximum reduction of about 6.75% is obtained at F_n=0.25.

As shown in Figure 12, the computed wave patterns also reflect the improved resistance. The opt1 hullform display remarkably reduced bow wave amplitudes at F_n=0.28. Furthermore, improvements are also found in the pressure distribution (see Figure 13,14 and 15).

From the above analysis, the success of the optimization process is confirmed. This is very large improvement in the resistance performance of ship.

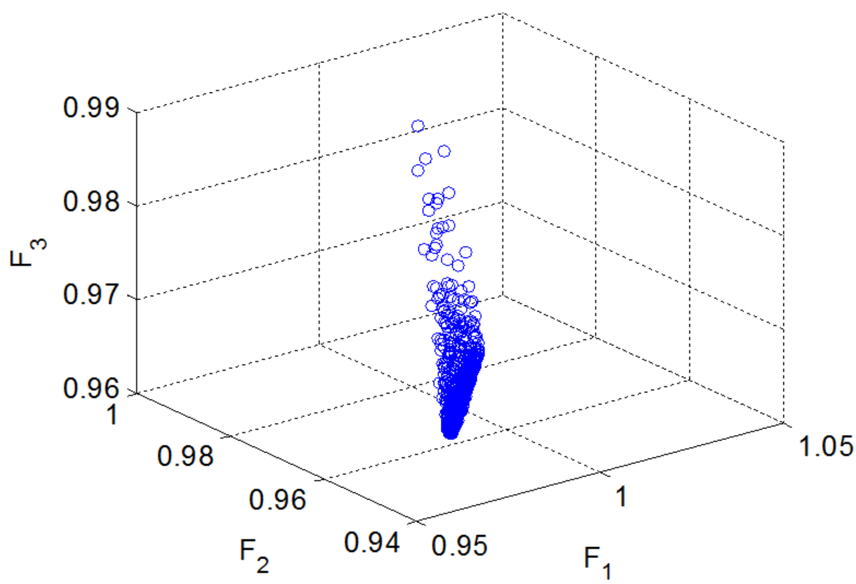


Figure 9: The Pareto front of the multi-speeds optimization problem

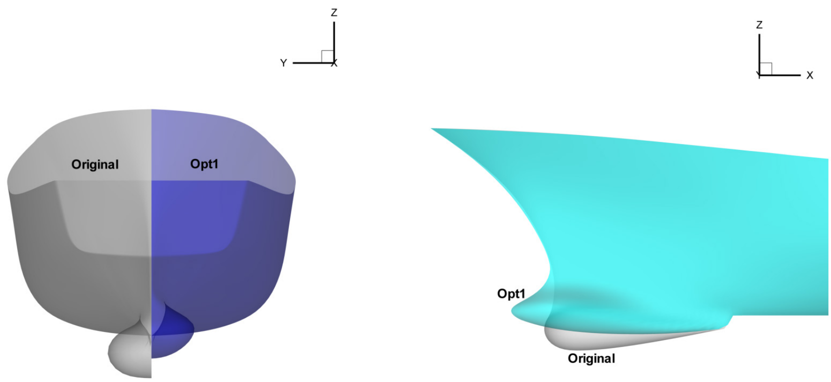


Figure 10: Comparison of the bow and bulb

Table 4: Comparison of the resistance components between the original and Opt1 models.

F_n	R_r(N)			R_t(N)		
	Original	Opt1	*Reduction*	Original	Opt1	*Reduction*
0.15	2.644	2.312	-12.55%	11.856	11.443	-3.48%
0.17	3.697	3.199	-13.46%	15.337	14.754	-3.80%
0.21	6.230	4.976	-20.14%	23.400	22.016	-5.91%
0.25	10.401	8.235	-20.82%	33.951	31.658	-6.75%
0.28	14.176	11.725	-17.29%	44.019	41.386	-5.98%
0.33	24.834	21.300	-14.23%	65.336	61.620	-5.69%
0.37	40.735	36.646	-10.04%	90.863	86.593	-4.70%

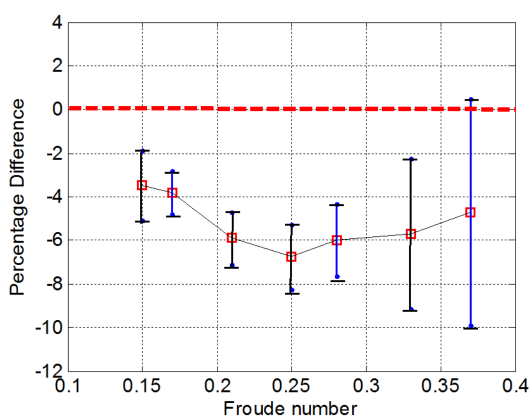


Figure 11: Resistance reduction (%) as a function of the Froude number for the optimized hullform (Error bars show the errors range between the computational and experimental results for original hullform).

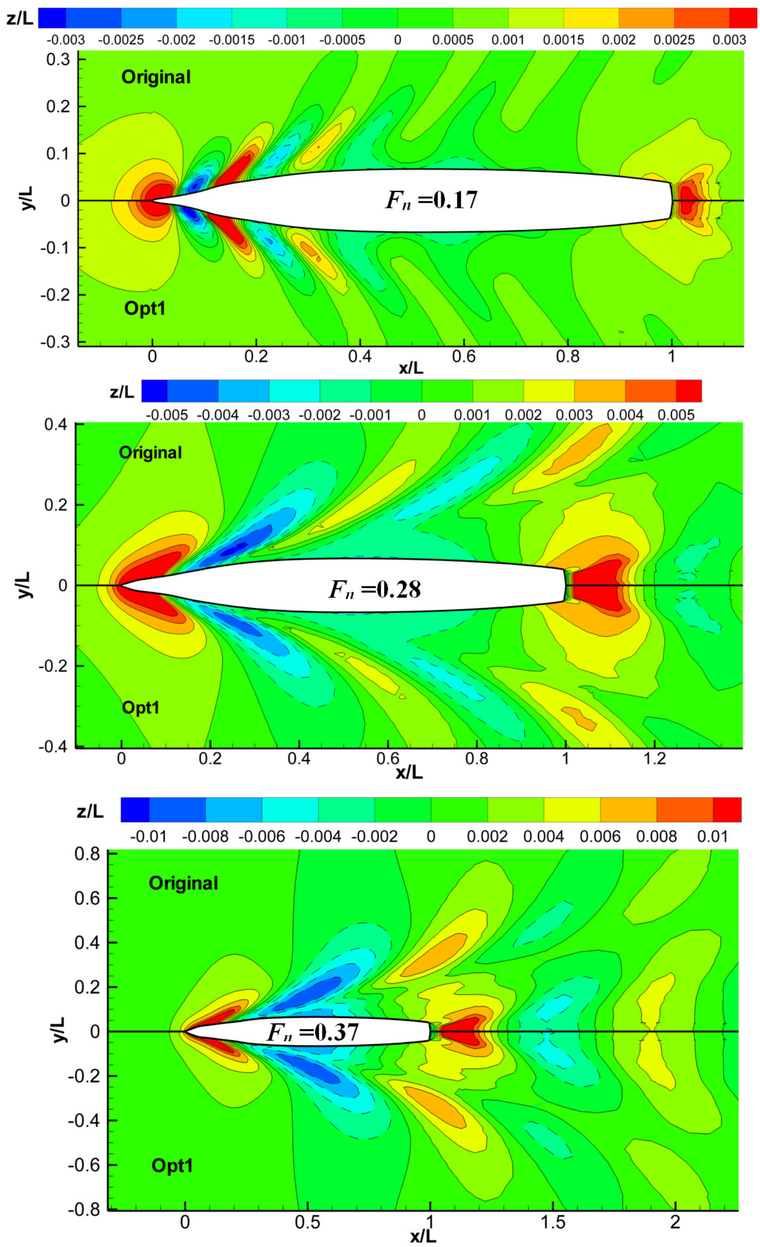


Figure 12: Comparison of wave contours between the original and opt1 hullform

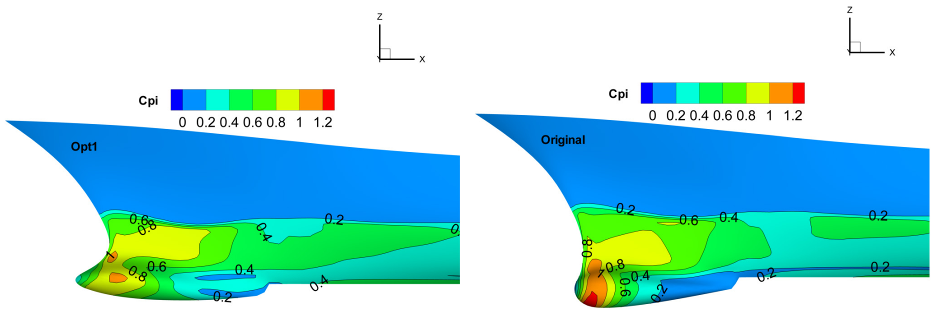


Figure 13: Surface dynamic pressure coefficient (C_{pi}) contours near the bow for the opt1 and original hullform (F_n=0.17)

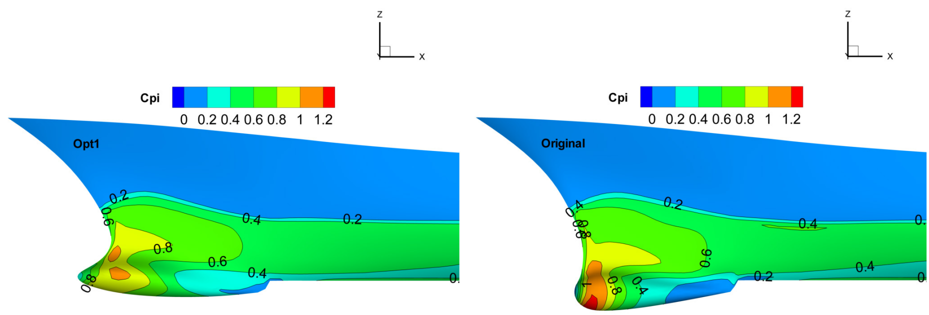


Figure 14: Surface dynamic pressure coefficient (C_{pi}) contours near the bow for the opt1 and original hullform (F_n =0.28)

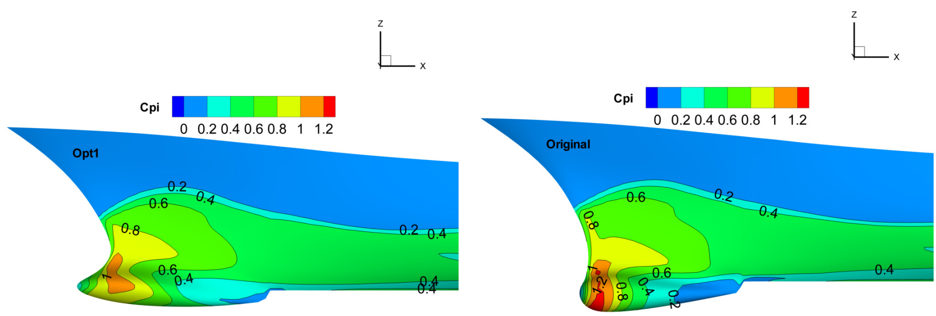


Figure 15: Surface dynamic pressure coefficient (C_{pi}) contours near the bow for the opt1 and original hullform (F_n =0.37)

6 Conclusions

An automatic hull-form design optimization framework has been established by integrating hull geometry modification and reconstruction approach, global optimization algorithms and CFD tools. And it has been applied to the challenging problem of the mid-high speed ship optimization.

The high-fidelity CFD solvers based on URANS are used for evaluating the total resistance during optimization cycles. The total resistance predicted by this CFD tool is in fairly good agreement with experimental measurements.

The global particle swarm optimization algorithm (PSO) is studied, and its initialization method and the inertia weight factor are improved, which provides effective and efficient scientific methods for solving the hull-form optimization design problem.

FFD hull modification approach has been developed; and it can be used to vary the hull form locally and globally, respectively. Only a small number of design variables are required to produce a new hull form from an original hull form.

The approximation strategy based on experimental design and response surface model is used for multi-objective optimization of bulb in order to reduce the computational cost. The results show that the reduction of the total resistance is about 6% for the optimized hullform at the design speed (F_n=0.28). This is very large improvement in the resistance performance, considering the small modifications allowed and the good initial performances of the original hull. And moreover, which will be very difficult to get by traditional design approaches guided only by the experience of the designers. The given practical examples demonstrate the practicability and superiority of the proposed SBD technique for the mid-high speed ship.

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