Optimization design of ship engine room structures based on sectionalized dynamic relaxation collaborative optimization method

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Abstract: Based on the standard collaborative optimization and aiming at its inherent flaws such as high sensitivity to the initial guess and slow convergence, this paper combines the collaborative optimization algorithm, the hybrid optimization algorithm, and the dynamic relaxation method to put forward a sectionalized dynamic relaxation collaborative optimization algorithm. The proposed algorithm can be applied in the multi-objective optimization of ship engine room structures. Meanwhile, the multi-objective collaborative optimization model of the main ship engine room is established to solve the static and dynamic, multidisciplinary and multi-objective optimization of ship engine room structures. Then, the collaborative optimization is validated through the Isight software to draw the optimal solution. It is shown that the step-by-step dynamic relaxation collaborative optimization algorithm achieves both accuracy and efficiency compared with that based on the genetic algorithm, which provides great references to the multidisciplinary and multi-objective design optimization of more complex structures in real projects.

Key words: ship engine room structure; collaborative optimization; hybrid algorithm; dynamic relaxation

CLC number: U663

0 Introduction

In order to make full consideration on the inter-coupling constraint characteristics among different disciplines during complex system design, Multi-disciplinary Design Optimization (MDO) appears to meet the increasing design demands. MDO strategy can be divided into single-level optimization method and multilevel optimization method. The existing single-level optimization methods mainly include All-At-Once (AAO), Multidisciplinary feasible (MDF) and Individual Discipline Feasible (IDF); multilevel optimization methods mainly consist of Collaborative Optimization (CO), Concurrent subspace optimization (CSSO) and Bi-Level Integrated System Synthesis (BLISS). Among these methods, owning to the adoption of decomposed modeling and parallel solving strategy, CO algorithm features in simple modeling, high solving efficiency, independent modeling and adaptable to distributed computing. Therefore, CO algorithm is an effective method for dealing with massive and complex engineering optimization and multidisciplinary design optimization problems.

As a newly developed optimization theory, CO has flaws as well, which also draws extensive attention and research. CO algorithm adopts the consistency equation constraint in system level optimization. Generally, the optimization problem cannot be convergent when the constraint requirements are not satisfied. Aiming at the problem of CO, Alexandrov and Lewis[1] provided the relaxation factor method which
relaxes the system level consistency equation constraints and changes the equation constraints into inequality form. But the relaxation factor is hard to be identified, which becomes another difficulty. From the perspective of geometry, Li et al.\(^5\) proposed dynamic relaxation based on the relaxation factor method, selecting relaxation factors by inconsistent information of discipline. Guo and Zeng\(^6\) divided the design space of optimization into three classes and valued each design space with different relaxations.

In recent years, CO algorithm has been widely applied in optimization design problems with complex structures. Balling et al.\(^3\) firstly adopted multidisciplinary optimization for solving multi–objective problems and applied CO in multi–objective problems. Li et al.\(^7\) researched how to transform multi–objective and multidisciplinary optimization into multi–objective synthesis problem reflecting the preference of designer. Jang et al.\(^8\) primarily introduced Pareto genetic algorithm into CO frame. Wang et al.\(^9\) applied the CO method and multi–objective genetic algorithm into the optimization design of body structure. Yang et al.\(^10\) proposed a CO and parto explorer (CO–PE) combinatorial optimization method, which is successfully applied in optimization design of satellite structure.

With certain particularity, the board thickness and aggregate of ship structure are formulated based on specifications, which changes optimization design variables to discrete variables; besides, due to the complex structure and numerous design variables of ship, the disciplines are intercoupled in general. Due to the consistency equation constraints of standard CO algorithm, the algorithm is hard to convergent. The discreteness of optimization design variables adds difficulty to the identification of relaxation factors of the fixed relaxation method. The convergence of CO algorithm based on genetic algorithm is slow. Targeting at the actual problems of engine room structure optimization and based on the flaws of the existing problems mentioned above, the hybrid optimization algorithm and dynamic relaxation method are planned to be applied in collaborative optimization algorithm. Hence, the Sectionalized Dynamic Relaxation Collaborative Optimization (SDRCO) algorithm is proposed in this paper. This algorithm sectionalizes the optimization stage into global search phase and partial search phase. Sectionalized optimization takes accounts of the stability and efficiency of the entire optimization process. Dynamic relaxation is adopted in both global phase and partial phase. But the relaxation factor of the partial phase is decreased to reduce the difference between system level and discipline level, ensuring the accuracy of the final optimization result. In addition, taken as an example, a ship engine room structure is optimization designed by the proposed SDRCO algorithm and genetic algorithm based CO algorithm (GA–CO). Through comparing and analyzing the optimization results of these two optimization methods, the efficient and accuracy of SDRCO algorithm are validated.

1 Improvement of CO algorithm

1.1 Standard CO algorithm

As an important multilevel optimization algorithm among multidisciplinary design optimization methods, collaborative optimization algorithm can decompose the complex engineering system design problem into bi–level optimization structures, including system level and discipline level according to the specific engineering division pattern. The optimization target of discipline level is to minimize the difference of optimization schemes between discipline level and system level according to the constraint requirements of discipline. System level optimization targets to optimize the objective of the entire optimization problem, ensuring the consistency of the coupling variables of each sub–discipline through equation constraint requirements. The mathematic model of standard CO is as follows:

1) System level optimization.

\[
\begin{align*}
\text{Min } & F(z) \\
\text{s.t. } & J_i^i(z) = \sum_{j=1}^{e} (x_{ij}^* - z_j^2) = 0; i = 1, 2, ..., n \\
\text{d.v. } & z = \left[z_i\right]; j = 1, 2, ..., e
\end{align*}
\]

(1)

where \( F(z) \) refers to objective function of the system level optimization; \( x_{ij}^* \) is optimal solution of the \( j^{th} \) shared variable of discipline level \( i; e \) indicates the number of shared variables of system level and discipline level; \( z_j \) is the \( j^{th} \) shared variable; \( J_i^i(z) \) refers to the consistency equation constraint requirements provided by discipline level \( i; n \) is the number of discipline level of optimization problem.

2) Discipline level optimization.

\[
\begin{align*}
\text{Min } & J_i(x) = \sum_{j=1}^{l} (x_{ij} - z_j^2); i = 1, 2, ..., n \\
\text{s.t. } & g(x_{ij}, x_{ik}) \leq 0 \\
& j = 1, 2, ..., e_i; k = 1, 2, ..., l_i \\
\text{d.v. } & x = \left[x_{ij}, x_{ik}\right]
\end{align*}
\]

(2)
where: $J_i(x_i)$ is optimization objective function of discipline level $J^i$; $x^i_j$ refers to the $j^{th}$ shared variable of discipline level $i$; $x_a$ represents partial design variable of discipline level $i$; $z^i_j$ is the $j^{th}$ shared variable delivered from system level to discipline level $i$; $g(x_j, x_a)$ refers to partial constraint requirements of discipline level.

First, system level assigns objective value $z^i_j$ of system level variable to discipline level. Under the condition of satisfying the self–constraints, each sub–discipline minimize the difference between coupling variable inside the discipline and objective value assigned by system through optimization. After that, the optimal solution is returned to the system level. Then system level optimizes the coupling variable under the consistency constraints. Through multi–iterations and information transfer on system level and discipline level, the optimal solution of design problem is finally figured out.

CO algorithm features in dealing the coupling problems among disciplines without system analysis in terms of the complex and massive engineering problems. However, CO algorithm has flaws as well owning to its structure. For example, the consistency constraint form of CO algorithm will greatly diminish the optimization search space, causing slow optimization convergence and even no convergence, or convergence results in partial solution. In order to improve the algorithm performance, the following measures are taken in this paper to improve the standard CO combining practical problems of ship structure optimization.

### 1.2 SDRCO algorithm

Aiming at the defects of standard CO algorithm, the following improvements are made:

1) To solve the problems of difficult CO convergence and partial optimal solution, the hybrid optimization strategy is adopted, which divides the entire optimization researching process into two optimization sections: global optimization phase and partial optimization phase. In the global optimization phase, as multi–objective optimization, system level optimization adopts Non–dominated Sorting Genetic Algorithm II (NSGA–II) of multi–objective intelligent optimization algorithm. Categorized as single–objective optimization, discipline level optimization applies Multi–Island Genetic Algorithm (MIGA) of single–objective optimization algorithm. Hence, the optimization searching can be carried out in the entire searching space from algorithm, avoiding partial optimal solution. After global optimization, when the convergence approaches global optimal solution, partial optimization search phase starts. System level adopts direct searching method, Hooke–Jeeves algorithm, while discipline level applies MIGA. In this way, the optimization convergence can be accelerated so as to obtain the optimal solution more quickly. Since the partial optimization phase adopts the single–objective direct searching method, Pareto set can be got after global search. It is necessary to weigh two objective functions (mass, acceleration) properly based on practical optimization problems, thus figuring out the needed optimal solution and the corresponding design points. And then these are taken as the initial point of partial optimization search. Finally, the optimal solution is figured out.

2) Given the specifications of board of ship structure, the thickness of board is recommended to be integer. Similarly, aggregate size has unified and regulated size specifications, which is integer in general. As a result, the values of the ship structure optimization design variables are fixed isolated integers, which means discrete variables. Consequently, the standard CO consistency is excessively constrained. In addition, it is relatively hard to determine the best relaxation factor when adopting fixed inequity relaxation factor. Therefore, the dynamic relaxation method based on hyper–ball subspace proposed by Li et al. is adopted in this paper. Taking two disciplinary problems as example, assuming that the optimal design point optimized by the first discipline in one iteration is $X_1$, and the optimal design point optimized by the second discipline is $X_2$, it is defined that:

$$\Delta = \| X_1 - X_2 \|$$

where $\Delta$ refers to inconsistent information between the two disciplines.

Let

$$S = (\lambda \Delta)^2$$

where $0.5 \leq \lambda \leq 1$. Consequently, new system level constraint is transformed to:

$$J^i_1(z) = \sum_{j=1}^{m_1} (z_j - x^i_j)^2 \leq S$$

$$J^i_2(z) = \sum_{j=1}^{m_2} (z_j - x^i_2)^2 \leq S$$

Eq. (3) represents two spheres in high–dimensional space centered by $X_1$ and $X_2$ with radius $S$. The feasible region of system level optimization refers to the intersection of the two spheres. As iteration per-
forms, the inconsistent information quantity $\Delta$ decreases continuously, resulting in the dynamic variation of $S$. Dynamic relaxation method can effectively overcome the solving difficulties generated by system level consistency equation constraint. In every iteration step, dynamic relaxation method can not only ensure the feasibility of system level optimization but also take the consistency requirements among disciplines into account.

In this paper, when applying dynamic relaxation method, the definition of inconsistent information will be adjusted according to the optimization phase. During the global optimization phase, global search is carried out in the whole space, avoiding the partial optimal solution. So $\lambda$ is valued to be 1 so as to broaden the searching space as much as possible and avoid partial solution of optimization. In the partial optimization phase, the solution set obtained from the optimization in global phase is near the optimal solution. In order to narrow the difference between discipline level and system level and guarantee the coupling of multidiscipline and high accuracy of optimization result, $\lambda$ can be decreased appropriately, which is $\lambda = 0.7$ in this paper.

After improving the standard CO algorithm, new SDRCO algorithm is obtained, of which the schematic diagram of core steps is presented in Fig. 1.

2 Multi-objective CO of ship engine room structure

The improved CO algorithm is applied to the multidisciplinary and multi-objective optimization of engine room structure of one ship. Besides, the optimization results of SDRCO algorithm and GA-CO algorithm are compared.

2.1 Mathematic model of optimization

The optimal structure is a model of the solid cabin of a real ship engine room. The length of ship is 18 m, the width is 16.4 m and the height is 7.8 m. The ship consists of double bottom, halfpace, deck, board side, longitudinal bulkhead, transverse bulkhead and other structures. Main engine, shear box, and other attached devices are installed on the inner bottom plates in the manner of mass point and MPC. The finite element model of main engine room is analyzed from statics and dynamics respectively. When computing the inherent frequency and response of engine room, the mass of structural entrained water is added to the outer bottom plating unit connecting water through the built-in virtual mass method of Patran software. Under the function of static load, engine room appears maximum positive stress $\sigma_{\text{max}} = 227$ MPa and maximum shear force $\tau_{\text{max}} = 112$ MPa; it is obtained that the maximum displacement response value of engine room is $d_{\text{max}} = 0.0548$ mm, the maximum velocity response value is $v_{\text{max}} = 2.96$ mm/s and the maximum acceleration response value is $a_{\text{max}} = 159$ mm/s when applying exciting force on the main engine; after modal calculation, the inherent first order frequency $f_1$ of the engine room equals 9.27 Hz.

1) Design variables.

In the engine room finite element model, there are 36 kinds of boards and 11 kinds of aggregates. The panel width $w$, web height $h$, panel thickness $t_1$ and web thickness $t_2$ of each kind of aggregate are segregated into 4 design parameters, 44 aggregate design parameters in total. The thickness $t$ of each board is counted as one design parameter, 36 board design parameters in total, 80 design parameters altogether. Sensitivity analysis is carried out on all the design variables from the response values such as mass, inherent frequency, positive stress, shear force, displacement, velocity and acceleration. As the sensitivity analysis results manifest that the mechanical properties of structure are mainly affected by the board thickness and aggregate web height. Therefore, 17 parameters are picked from 80 design parameters as optimization design variables, among which $x_1$-$x_{13}$ refer to the main board thickness and $x_{14}$-$x_{17}$ refer to the main aggregate web height.

2) Constraint conditions.

In the system level optimization, consistency constraints $J_1$ and $J_2$ are taken as the constraint re-
requirements; as for the statics discipline optimization, the maximum positive stress $\sigma_{\text{max}}$ and maximum shear force $\tau_{\text{max}}$ are taken as the constraint requirements; in dynamics discipline optimization, the first order inherent frequency $f_j$, maximum displacement response $d_{\text{max}}$ and the maximum velocity response $v_{\text{max}}$ are taken as constraint conditions.

3) Objective function.

In system level optimization, during the global optimization phase, structural mass $m$ and maximum acceleration response $a_{\text{max}}$ act as the multi-objective functions. During partial optimization phase, the weights of 2 objective functions are identified based on the global optimization result. Then the weight values are taken as the objective function of partial optimization phase. In this paper, the weight coefficient of engine room structure mass $m$ is 0.35, and the maximum weight coefficient of acceleration response $a_{\text{max}}$ equals 0.65. In the statics and dynamics discipline level optimization, the consistency constraints $J_1$ and $J_2$ are taken as objective functions.

According to the above description, the mathematical model of engine room structure multidisciplinary and multi-objective CO constructed by SDRCO algorithm is as follows.

**System level:**

$$\min F(z) = (m, a_{\text{max}})$$
$$F(z) = 0.35 \times m + 0.65 \times a_{\text{max}}$$

s.t. $J_1(z) = \sum_{j=1}^{n}(z_j - x_{j\text{opt}})^2 \leq S$

$J_2(z) = \sum_{j=1}^{n}(z_j - x_{j\text{opt}})^2 \leq S$

$$\text{d.v. } z = [z]$$

(6)

**Statics discipline:**

$$\min J_1 = \sum_{j=1}^{n}(x_{ij} - z_j)^2$$

s.t. $\sigma_{\text{max}} \leq [\sigma]$

$\tau_{\text{max}} \leq [\tau]$

$$\text{d.v. } x_i = [x_{ij}, x_{ik}]$$

(7)

**Dynamics discipline:**

$$\min J_2 = \sum_{j=1}^{n}(x_{j2} - z_j)^2$$

s.t. $f_j \geq [f]$

$d_{\text{max}} \leq [d]$

$v_{\text{max}} \leq [v]$

$$\text{d.v. } x_j = [x_{j2}, x_{j3}]$$

(8)

### 2.2 Collaborative optimization process

In this paper, optimization software Isight is adopted to integrate the pre-processing software Patran and finite element computation software Nastran for the iteration calculation. Owning to the complicated finite element model of engine room, long calculation duration of frequency response in particular, the optimization efficiency is affected. As a result, the radial basis function approximation model is applied to replace finite element calculation process so as to increase the optimization efficiency. Radial basis function takes the Euclidean distances between the points to be tested and sample points as independent variables. Through Euclidean distance, radial basis function can easily transform multi-dimensional problem into one-dimensional problem with Euclidean distance as independent variable.

First of all, super Latin test design method is adopted for sensitivity analysis of design variables, and design variables are selected; then, super Latin test design method is applied for collecting the sample points and constructing approximation model; finally, the collaborative optimization structure is built. In the global search phase, NSGA-II is employed for global search until the design points approach the optimal solution. After that, the weight is determined according to the optimization requirements. One group of optimal solutions and their corresponding design points can be found out, which are taken as the initial points of partial search phase. Then, Hooke-Jeeves algorithm is adopted for the partial search, and the optimal solution of optimization design is finally found out. By adopting SDRCO algorithm, the flow chart of the multi-objective CO of engine room structure is presented in Fig. 2.

#### 2.3 Comparison of optimization results

SDRCO and GA-CO algorithms are respectively applied for multi-objective optimization of ship engine room structure. When using SDRCO algorithm, after finishing global optimization and obtaining Pareto solution set, a group of solutions is figured out according to the identified weight coefficients. In addition, the optimization results are taken as the initial design variable in partial optimization phase for optimization, obtaining the final optimal solution. Then, the final optimal solution is compared with optimal solution solved by CO algorithm based on genetic algorithm.

Based on SDRCO algorithm, Pareto solution set figured out in global optimization phase is shown in Fig. 3, and the iteration process of partial optimization phase is presented in Fig. 4.
Pareto solution set optimized by GA-CO algo¬
rithm is presented in Fig. 5.

The statics and dynamics response optimal solu-
tions of two algorithms, as well as the value ranges of
design variables before and after optimization are
presented in Table 1 and Table 2.

According to the contrast analysis of the optimiza-
tion results of two algorithms, it can be concluded as
follows:

1) It can be known from optimization results that
after the optimization of SDRCO algorithm pro-
posed in this paper, 2 optimal objective values are ob-
tained after 2 200 iterations in 2 phases, which are: the
structure mass is optimized to 2 830.2 t, declining by
about 13.7% compared to the initial value; the maxi-
mum acceleration decreases to 111.9 mm/s^2, reduc-
ing by 29.6% compared with the initial value, of
which the optimization effect is obvious.

2) It can be discovered by comparing the optimiza-
Table 1 The comparison between results based on SDRCO algorithm and GA–CO algorithm

<table>
<thead>
<tr>
<th>Parameters</th>
<th>SDRCO</th>
<th>GA–CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>m/t</td>
<td>3 280.0</td>
<td>2 830.2</td>
</tr>
<tr>
<td>$a_{\text{max}}$ (mm/s$^2$)</td>
<td>158.8</td>
<td>119.9</td>
</tr>
<tr>
<td>Weighted value</td>
<td>1 251.2</td>
<td>1 063.3</td>
</tr>
<tr>
<td>$\sigma_{\text{max}}$ (MPa)</td>
<td>227.1</td>
<td>224.5</td>
</tr>
<tr>
<td>$\tau_{\text{max}}$ (MPa)</td>
<td>113.9</td>
<td>113.7</td>
</tr>
<tr>
<td>$J_1$ (Hz)</td>
<td>9.272</td>
<td>9.385</td>
</tr>
<tr>
<td>$d_{\text{max}}$ (mm)</td>
<td>0.0548</td>
<td>0.0550</td>
</tr>
<tr>
<td>$v_{\text{max}}$ (mm/s)</td>
<td>2.962</td>
<td>2.973</td>
</tr>
<tr>
<td>Final value</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 600+600</td>
<td>3 200</td>
</tr>
</tbody>
</table>

Table 2 The comparison of design variables between SDRCO algorithm and GA–CO algorithm

<table>
<thead>
<tr>
<th>Design variable</th>
<th>Initial value</th>
<th>Final value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>24</td>
<td>19</td>
</tr>
<tr>
<td>$x_2$</td>
<td>20</td>
<td>17</td>
</tr>
<tr>
<td>$x_3$</td>
<td>12</td>
<td>11</td>
</tr>
<tr>
<td>$x_4$</td>
<td>20</td>
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<td>$x_5$</td>
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<td>$x_6$</td>
<td>16</td>
<td>17</td>
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<td>$x_7$</td>
<td>20</td>
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</tr>
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<td>$x_8$</td>
<td>24</td>
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<td>$x_9$</td>
<td>20</td>
<td>20</td>
</tr>
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<td>$x_{10}$</td>
<td>16</td>
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</tr>
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<td>$x_{11}$</td>
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<td>$x_{12}$</td>
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<tr>
<td>$x_{14}$</td>
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<td>160</td>
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<td>$x_{15}$</td>
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<td>$x_{16}$</td>
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<td>260</td>
</tr>
<tr>
<td>$x_{17}$</td>
<td>180</td>
<td>150</td>
</tr>
</tbody>
</table>

3) SDRCO algorithm adopts sectionalized dynamic relaxation, narrowing the dynamic relaxation factors in partial optimization phase and reducing the difference between system level and discipline level. It can be found from optimization results that the differences of two sub-disciplines and system level are both 1, which are smaller than that of GA–CO algorithm, ensuring the accuracy of optimization results.

3 Conclusions

In this paper, considering the inherent defects of standard CO algorithm, such as convergence difficulty and partial optimal solution, as well as the particularity of practical problems in ship engine room structure optimization, two improvements are carried out aiming at the standard CO: one is to apply hybrid optimization algorithm, sectionalizing the problem into global optimization and partial optimization. In the global phase, global multi-objective optimization method is adopted to guarantee the convergence. While partial phase adopts direct searching method to accelerate the convergence and enhance the stability of algorithm; the other is to adopt sectionalized dynamic relaxation method to replace consistency constraint and fixed relaxation factor method. In the global phase, dynamic relaxation factor takes the maximum value to avoid trapping in partial optimal solution. In the partial phase, relaxation factor is declined to ensure the accuracy of result. Thus, SDRCO algorithm is improved. By using this method, the main engine room structure of one ship is optimized by multidiscipline and multi-objective. First, it is discovered after SDRCO optimization that both the mass and acceleration of two objective structures are greatly declined. The evident effect of optimization indicates the effectiveness of this method; secondly, by comparing SDRCO algorithm proposed in this paper and GA–CO algorithm, it is discovered that with fewer iterations, SDRCO algorithm achieves better optimization result, which verifies the efficiency of the algorithm; besides, by applying sectionalized dynamic relaxation, the difference between system level and discipline level in partial optimization phase of SDRCO algorithm is smaller, demonstrating that SDRCO algorithm has higher accuracy. It is thus clear that SDRCO algorithm is of better applicability in multidisciplinary and multi-objective optimization problems of complex ship structure in practical engineering.

References


基于分段动态松驰协同优化算法的
船舶机舱结构优化设计

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摘 要：基于标准的协同优化算法, 针对其对初始点敏感, 收敛慢等固有缺陷, 将协同优化算法与混合优化算法及动态松驰法相结合, 提出分段动态松驰协同优化算法, 并将该算法应用到船舶机舱结构多目标优化问题中。针对船舶机舱结构静、动态多学科多目标优化问题, 建立主机舱结构的多目标协同优化模型。在 Isight 优化软件中采用改进的分段动态松驰协同优化算法, 对船舶机舱结构进行静、动态多学科多目标协同优化设计, 得到优化设计的最优解。优化结果表明, 相对于基于遗传算法的协同优化算法, 分段动态松驰协同优化算法兼顾了优化的高效性和准确性, 对于实际工程中更加复杂的多学科多目标结构优化具有一定的参考价值。

关键词：船舶机舱结构；协同优化；混合算法；动态松驰