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Hierarchical Progressive Optimization for Aerodynamic/Stealth Conceptual Design Based on Generalized Parametric Modelling and Sensitivity Analysis

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Abstract

A hierarchical progressive optimization approach is proposed for multidisciplinary optimal design by integrating with generalized parametric modeling and sensitivity analysis. The framework includes the following: (1) to set up a generalized parametric model for the geometric parameters of flight vehicles with different levels, (2) to reduce the number of design parameters using sensitivity analysis method and (3) to use the gradual optimization design method to solve the problem of integrated aerodynamic-stealth optimization design. The results from the application on the configuration optimization of an aircraft demonstrate that the hierarchical progressive optimization increases the fitness of the optimization design by 51.1% and improves the conceptual design efficiency.

Keywords: aircraft design, hierarchical progressive optimization, generalized parameters, sensitivity analysis, multidisciplinary optimization

1. Introduction

Stealth is a significant development trend of weaponry in the future. Because the requirements of aerodynamics/stealth conceptual design are often contradictory, in order to obtain aircraft configuration with good aerodynamic/stealth performance, it is necessary to conduct the studies on multidisciplinary optimization of aerodynamics and stealth.

With the development of computing technology, the integration of high fidelity numerical simulation and multidisciplinary optimization (MDO) has become common for the conceptual

design of aircraft configuration [1]. However, the researches mostly rely on the empirical approach to realize the multidisciplinary concept design.

In view of practical engineering application, there is an inevitable trend to integrate CAD modeling into multidisciplinary optimization design framework. This parametric modeling necessarily involves more parameters for the optimization of aerodynamics and stealth than those only for aerodynamics design. The resultant extra-optimization design due to the additional parameters would reduce the optimization efficiency. Sensitivity analysis is, therefore, necessary to classify the generalized parameters. Moreover, in comparison to the conventional optimization method, MDO requires available treatment to the coupling of aerodynamics and stealth.

The present study aims to conduct rapid conceptual design for aerodynamics/stealth optimization of a four-tailed aircraft configuration. Firstly, parametric modeling method is proposed to describe aerodynamic/stealth multidisciplinary characteristics. Secondly, hierarchical progressive optimization process integrated with sensitivity analysis is proposed to achieve rapid conceptual design. Finally, the methods are applied to rapid optimization for conceptual design of aerodynamic/stealth of an aircraft. Therefore, this hierarchical progressive optimization approach integrated generalized parametric modeling and sensitivity analysis is expected to simplify the optimization and improve the design efficiency, which has the following advantages:

- (1) Combined with the progressive process of CAD modeling, it can extract the parameters to describe both aerodynamics and stealth and then provide generalized parameters for hierarchical progressive design.
- (2) By classifying the generalized parameters with sensitivity analysis, it can not only reduce the complexity and workload of the optimization but also guide the optimization based on the parametric sensitivity information.

2. Hierarchical progressive optimization

The main idea of MDO is to integrate the knowledge of different disciplines in complex design systems, to fully consider the interaction and coupling between the disciplines, to organize the design of the whole system with effective design and optimization strategies, to reduce the design cycle by realizing modular parallel design of different disciplines, to exploit design potential by considering interdisciplinary coupling and to select and evaluate the optimization design by systematic integrated analysis.

As shown in **Figure 1**, traditional optimization design is the case, where $N = 1$. This approach features simple process and relatively low optimization efficiency. In order to improve the efficiency of MDO design, hierarchical progressive optimization (shown in **Figure 1**) is proposed for engineering practice.

The hierarchical progressive optimization is capable of dividing the enormous design space into several subspaces; each dramatically reduces the number of optimization parameters and

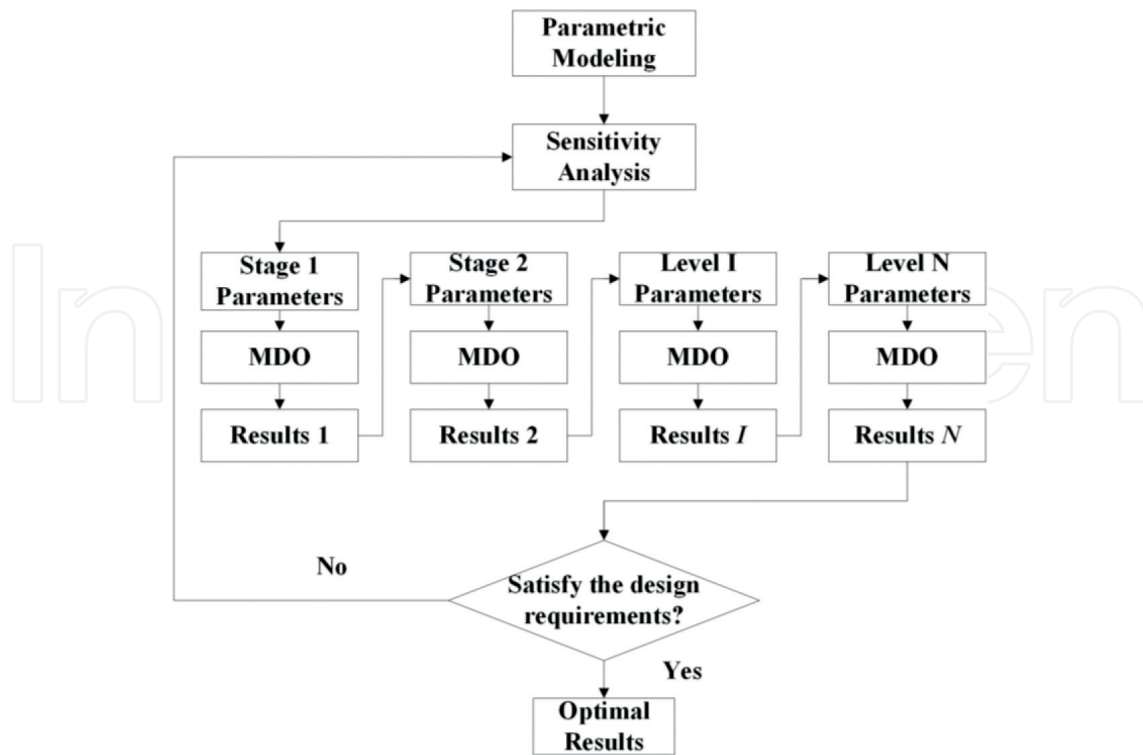


Figure 1. The schematic diagram of hierarchical progressive optimization.

constraint conditions, which significantly reduce the complexity of optimization. The optimal solution of the design can be obtained by iteration among the subspace. In order to exert this design superiority, it is crucial to construct a suitable optimization design system to adapt to the hierarchical progressive optimization design framework.

2.1. Differential evolution (DE) method

A differential evolution (DE) algorithm is a stochastic heuristic search algorithm to simulate the biological population evolution in nature of “survival of the fittest” principle. It was proposed by Storn and Price [2] to improve the genetic algorithm. Due to its simplicity, ease of use, robustness and powerful global search capability, differential evolution has been successfully applied in many fields.

The basic idea is to generate a random initial population in the beginning, to sum up with vector weighted of any two and third individuals according to specific rules to generate new individuals. By comparing this new individual fitness and a predetermined individual, the better individual will be survived. Through the continuous iteration of retaining the excellent individuals and eliminating the inferior individuals, the search process is directed to approximate the optimal solution.

The differential evolution algorithm has the characteristics of memorizing optimal solution of individual and sharing information within the population, and its essence is a greedy genetic algorithm with real coding based on the idea of preserving optimality. Compared with the traditional optimization method, it has the following main features:

1. It starts to search from a group, i.e., multiple points rather than a point, which can avoid the defects of retention at local optimum and thus has high probability to find the global optimal solutions.
2. The evolutionary rule is based on adaptive information and without any other additional auxiliary information (such as requiring the function to be derivable or continuous), which greatly extends its application range and inherits the advantages of genetic algorithm.
3. It has inherent parallelism, which makes it very suitable for massively parallel distributed processing and therefore reducing the time cost.
4. Using probability transfer rules to search, this is the improvement of the genetic algorithm, to ensure that it quickly finds the optimal solutions.

Differential evolution algorithm is an evolutionary algorithm based on real coding, which is similar to other evolutionary algorithms in structure. It consists of three basic operations: mutation, crossover and selection.

Let suppose that $X_i(t)$ is the i th individual in the population t , then

$$X_i^t = (X_{i1}^t, X_{i2}^t, \dots, X_{in}^t), \quad i = 1, 2, \dots, M; t = 1, 2, \dots, t_{\max} \quad (1)$$

where n is the chromosome number of the individual (i.e., the number of variables in the vector), M is the population number and t_{\max} is the maximum number of evolution.

The detailed description of the basic strategies [2] is as follows:

1. Initial population:

In an n -dimensional space, M individuals that satisfy constraint conditions are randomly generated:

$$X_{ij}^0 = \text{rand}_{ij}(0, 1)(X_{ij}^U - X_{ij}^L) + X_{ij}^L, \quad i = 1, 2, \dots, M; j = 1, 2, \dots, n \quad (2)$$

where X_j^U and X_j^L are the upper and lower bounds of j chromosome, respectively; $\text{rand}_{ij}(0, 1)$ is a random decimal between $[0, 1]$.

2. Mutation:

The most basic variant of differential evolution algorithm is the parent difference vector; each vector pair includes two different individuals in the parent (generation t) population. The difference vector is defined as

$$D_{r1,2} = X_{r1}^t - X_{r2}^t \quad (3)$$

$r1$ and $r2$ represent the index numbers of two different individuals in a population. The differential vectors are added to another randomly selected vector to generate the variation vectors. For each objective vector X_i^t , mutation manipulation is used as

$$v_i^{t+1} = X_{r3}^t + F*(X_{r1}^t - X_{r2}^t) \quad (4)$$

$r1, r2, r3 \in \{1, 2, \dots, NP\}$ is an integer different from each other, and $r1, r2, r3$ is different from the current objective vector index i , so the number of population $NP \geq 4$. F is a scaling factor with a range of $[0, 2]$ to control the differential vector scaling.

3. Crossover:

The crossover operation is used to crossover the objective vector individuals X_i^t in the population with the mutation vector v_i^{t+1} to generate the test individuals u_i^{t+1} . In order to ensure the evolution of the individuals, at least one of v_i^{t+1} is contributed to u_i^{t+1} by random selection, while for others, a crossover probability factor CR can be used to decide which one of v_i^{t+1} or X_i^t is contributed to u_i^{t+1} . The equation of crossover operation is

$$u_{ij}^{t+1} = \begin{cases} v_{ij}^{t+1}, randl_{ij} \leq CR \text{ or } j = rand(i) \\ x_{ij}^t, randl_{ij} > CR \text{ or } j \neq rand(i) \end{cases} \quad (5)$$

where $randl_{ij} \in [0, 1]$ is the random number in uniform distribution, j represents the j th variable (gene), and CR is the crossover probability constant with the range of $[0, 1]$, and the length is predetermined. $rand(i) \in [1, 2, \dots, n]$ is the index of dimension variables for random selection to ensure that at least one-dimension variable is contributed by the variation vector. Otherwise, the test vector may be the same as the objective vector and cannot generate new individuals.

4. Selection:

DE uses the greedy search strategy to compete the test individuals u_i^{t+1} generated by mutation and crossover operations with X_i^t , and the fitness u_i^{t+1} is chosen as the offspring only when it is better; otherwise, X_i^t will be directly used as the offspring. For example, the equation of operation for minimization optimization is chosen as

$$X_i^{t+1} = \begin{cases} u_i^{t+1}, f(u_i^{t+1}) < f(X_i^t) \\ X_i^t, f(u_i^{t+1}) \geq f(X_i^t) \end{cases} \quad (6)$$

Execute the above four operations repeatedly until the maximum number of evolution t_{max} is reached.

2.2. Optimization strategy

The mathematical model of the multi-objective optimization problem (MOP) [3] widely used and accepted in multi-objective optimization is defined as follows:

$$\begin{aligned} \min \quad & y = f(x) = (f_1(x), f_2(x), \dots, f_k(x)) \\ \text{s.t.} \quad & e(x) = (e_1(x), e_2(x), \dots, e_m(x)) \leq 0 \\ \text{where} \quad & x = (x_1, x_2, \dots, x_n) \in X \\ & y = (y_1, y_2, \dots, y_k) \in Y \end{aligned} \quad (7)$$

The model consists of n parameters (decision variables), K objective functions and m constraints. The objective function and constraints are the functions of decision variables. Among them, x represents the decision vector, y represents the objective vector, X represents the decision space formed by the decision vector x , and Y represents the objective space formed by the objective function y , and the constraint condition determines the feasible range of the decision vector.

Modern aircraft not only has high aerodynamic performance but also requires good stealth performance. At present, reducing radar cross section (RCS) is the most important part of stealth technology. Aircraft design must take into account both the high aerodynamic efficiency and low RCS requirements in the configuration design. However, the requirements of the two are often contradictory.

Through an auto-adjusting weighted object (AWO) optimization method [3], the multi-objective optimization problem is transformed into the optimization strategy of the single objective problem, which can effectively solve the design requirements of such contradictions.

Its advantage is that in the process of optimization, certain adjustments can be done to improve the objective function for each subject according to the rate of information. It can avoid the suppression of the further optimization of other objective functions due to the extremely quick changes of some objective function and therefore obtain an effective solution with relatively synchronous optimization for all the subject object functions.

AWO is used as follows:

$$\Delta Obj_i = \frac{Obj_i - R_e Obj_i}{|R_e Obj_i|} \quad (i = 1, 2, \dots, n) \quad (8)$$

$$Globj_i = \sum_{i=1}^n C_i Obj_i, \quad \sum_{i=1}^n C_i = 1 \quad (9)$$

where $R_e Obj_i$ is the objective reference value, Obj_i is the single subject fitness, $Globj_i$ is the comprehensive performance (fitness), and C_i is the weighted coefficient. For any i , if $\Delta Obj_i \leq \delta_0$, then accept the optimal solution and change the objective reference, or if $R_e Obj_i = Obj_i$, then give up the optimal solution. δ_0 is the control value of objective optimization, which generally takes $\delta_0 \leq 0.1$. If the optimal solution is accepted, the weighted coefficient is adjusted:

$$\begin{aligned} C_{better} &= C_{better} - \delta_c \\ C_{worse} &= C_{worse} + \delta_c \end{aligned} \quad (10)$$

where δ_c is the adjustment step size of the weighted coefficient, which is set as $\delta_c = 0.1 \times 0.9 L$, and L is the optimized step number. C_{better} is the weighted coefficient to optimize the better objective, and C_{worse} is the weighted coefficient to optimize the worse objective.

Most optimization problems contain some constraints, which divide the decision space into two parts: feasible and infeasible. The task of constrained multi-objective optimization is transformed into finding the Pareto optimal solution in the feasible region of the decision

space. The penalty function method [4] is used to deal with the fitness function with the constrained problem, and the individuals beyond the constraint are discarded.

Penalty function method is the most commonly used method for solving constrained optimization problems. By calculating the constraint offset of the solution, the objective function is punished, and the constrained problem is transformed into an unconstrained optimization problem. Before computing the constraint offset, the constraint function is normalized as $e_j(x) \leq 0, j = 1, 2, \dots, M$ so that the offset of the constraint function j is defined as the form of the following vector:

$$w_j(x) = \begin{cases} |e_j(x)|, & \text{if } e_j(x) > 0 \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

The sum of the offset of the vector x on each constraint function is called the total offset:

$$\Omega(x) = \sum_{j=1}^M w_j(x) \quad (12)$$

For the minimization problem, the objective function value of the solution vector x will be modified as follows:

$$F_m(x) = f_m(x) + R_m \Omega(x), m = 1, 2, \dots, K \quad (13)$$

where $f_m(x)$ is the function value of the individual i under the unconstrained condition on the m objective and R_m is the penalty function coefficient, which is used to balance the differences caused by the different dimensions of each objective. From the above definition, we can see that when $\Omega(x) = 0$, x is a feasible solution. When x is an infeasible solution, the farther away from the feasible domain, the greater the value of the objective function, the more penalties. After obtaining the objective function value after penalty, the unconstrained multi-objective optimization method can be used to solve the Pareto optimal solution. For example, for m constraints:

$$\varphi_j(x) \geq C_j, j = 1, \dots, m \quad (14)$$

$$P_j = \begin{cases} 0, & \varphi_j < C_j \\ 1, & \varphi_j \geq C_j \end{cases} \quad (15)$$

The fitness is adjusted to be $Y_i = Globj_i \prod_{i=1}^n P_j$, where $Globj_i$ is the global performance (fitness).

3. Generalized parametric modeling

Parameters are both the objects for multidisciplinary design and the manifestation of the design results. Single disciplinary parametric modeling tends to ignore the requirements of

multidisciplinary optimization as well as the requirements of other disciplines. However, the multidisciplinary parametric modeling is expected to not only integrate with various disciplines but also meet the requirements of practical optimization. Therefore, aerodynamics/stealth multidisciplinary optimization urges the construction of a parametric system that can meet the requirements of both aerodynamics and stealth discipline as well as to adapt to practical optimization design.

3.1. Generalize parameter

Generalized parameters are proposed to assist the increasingly complicated multidisciplinary design process of aircraft. They are necessary to reflect the discipline characteristics such as aerodynamics and stealth more than their appearance of the aspect of configuration. The whole generalized parametric system is divided into four dimensions, namely, design phase, component, discipline and design. It is constructed for aerodynamics/stealth optimization by classifying the design phases based on the progressive features of CAD modeling and analyzing the component characteristics of the major components (fuselage, wing, etc.).

3.2. Parametric modeling

Parametric modeling is the direct source of design parameters in multidisciplinary optimization design and the prerequisite of analysis and optimization design. Based on the integrated consideration of different requirements of aerodynamics and stealth on modeling parameters, the following modeling parameters of three levels is extracted in accordance with the hierarchy and progressive of CAD modeling:

(1) Twenty-seven general profile parameters: These parameters are used to describe the main profile of the fuselage cross section, shape characteristics, as well as installation angle and dihedral angle of wings and tails. The fuselage parameters include deviation angle of the head longitudinal line, head length, length of the head transition section, length of the intermediate section, tail length, the magnification ratio of fuselage cross section, and the magnification ratio of the tail cross section. The wing parameters include aspect ratio, root chord length, sweepback angle, taper, installation angle, and dihedral angle. Among them, some parameters of angle are introduced in view of stealth, as is shown in **Figure 2**; the height of head cross section is controlled by the upward deflection angle of head longitudinal line $\angle AOE$ and the downward

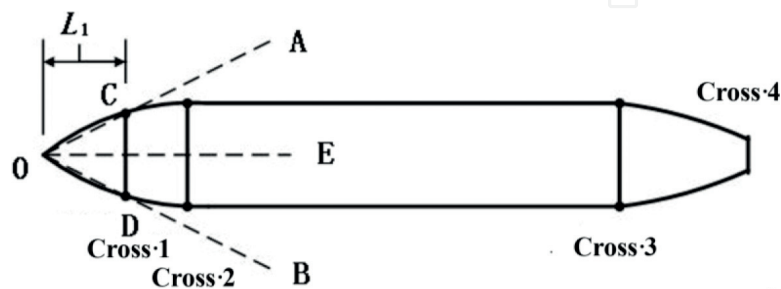


Figure 2. Geometric parameters of fuselage sections.

deflection angle of head longitudinal line $\angle BOE$ and head length $L1$. The parametric relation is indicated by Eq. 16:

$$|CD| = |L_1| \cdot (tg \angle AOE + tg \angle BOE) \quad (16)$$

(2) Twenty major control parameters of cross sections: As shown in **Figure 2**, the fuselage is controlled by four control cross sections along the axis. The major control parameters refer to the line segment ratios, angles, etc. of the main edges of the control cross sections. As shown in **Figure 3**, the position of the edge endpoint F is determined by the line segment ratio between BF and BC , while that of G is determined by the endpoint F and $\angle CFG$.

(3) Eighty-four profile modifying parameters of cross sections: Based on the specific edge positions of the cross sections that have been obtained, the conics are applied to modify the cross section edges. The conic control endpoints are obtained by distributing the line segment ratios on each edge; then the conics are constructed between the endpoints to obtain the specific profile of the cross sections. For example, points ①~⑥ in **Figure 3** are controlled by line segment ratios. By altering the position of control points and shape parameters of the conics, the cross sections can be expressed as various shapes, such as a circle, polygon and so on, which can meet the requirements of stealth on cross section shapes as the CAD examples shown in **Figure 4**.

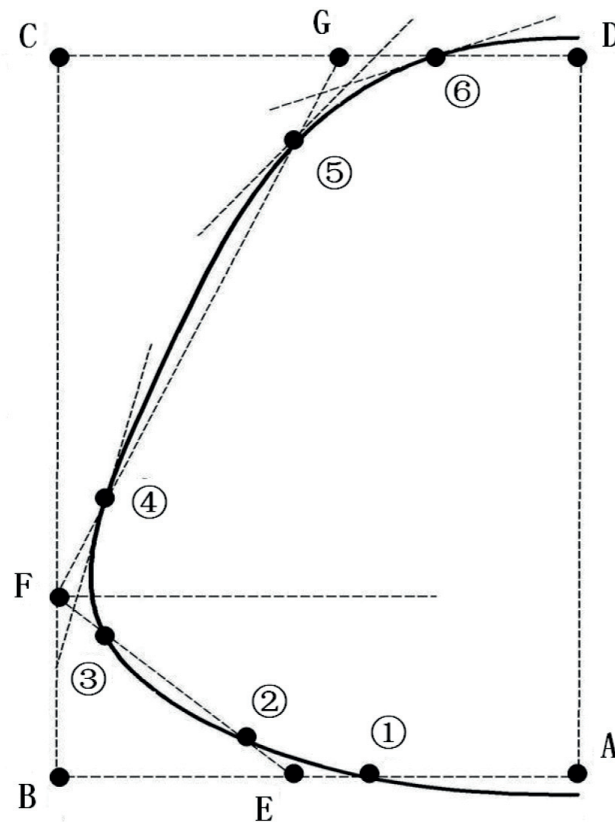


Figure 3. Geometric parameters of cross sections.

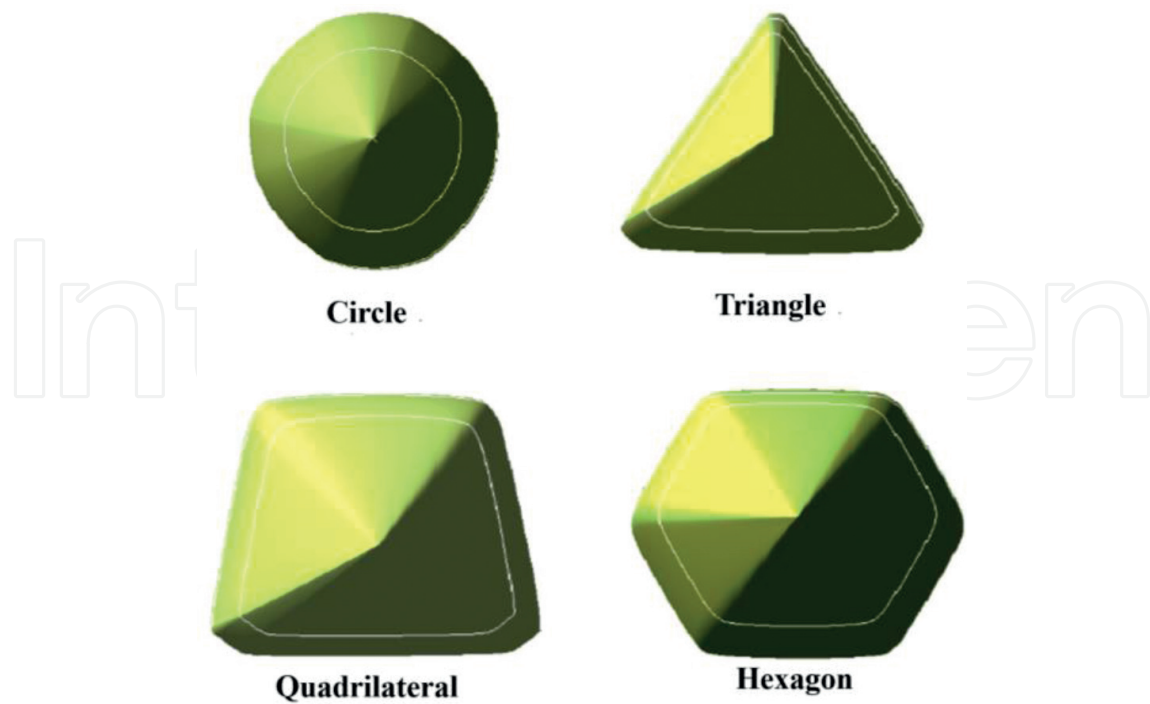


Figure 4. Several shapes of body sections.

In general, the width and height of each cross section can be altered through general profile parameters. Then, the edge position of the cross sections can be changed by adjusting the major control parameters of the cross section. Finally, extra padding is done at the head, fuselage transition section, fuselage and tail through interpolation. This parametric modeling method features clear with progressive modeling and hierarchical parameter, which is highly applicable for hierarchical progressive optimization.

3.3. Generalized parameter system

Based on the characteristics of the design phase, components and disciplines, the generalized parameter system with a total number of 131 including 3-level modeling parameters is listed in **Table 1**. In order to adapt to hierarchical progressive optimization, the sensitivity analysis is applied to classify the design parameters.

Design phase	Parameters	Numbers	Components	Disciplines
Layout	Layout parameters	6	Fuselage and wing	Aerodynamics/stealth
Component	Profile parameters	27	Fuselage and wing	Aerodynamics/stealth
Component	Control parameters	20	Fuselage	Aerodynamics/stealth
Component	Modification parameters	84	Fuselage	Stealth

Table 1. Design parameters.

4. Sensitivity analysis

Sensitivity is the derivative information of system parameters versus design parameters, and it reflects the variation trend and degree. The sensitivity analysis [5] can determine the affecting magnitude of system design parameters on the objective function and guide the process of optimization design. N points in the design range are uniformly distributed, and then the sensitivity is analyzed by central difference scheme, as shown in Eq. 17:

$$\frac{dF}{dX} = \frac{1}{N} \sum_{i=1}^N \left| \frac{F(X_i + \Delta X_i) - F(X_i - \Delta X_i)}{2\Delta X_i} + O((\Delta X_i)^2) \right| \approx \frac{1}{N} \sum_{i=1}^N \left| \frac{F(X_i + \Delta X_i) - F(X_i - \Delta X_i)}{2\Delta X_i} \right| \quad (17)$$

In consistent with the hierarchy features of generalized parameters, the two-round sensitivity analysis method is proposed in **Figure 5**. In the first round, the individual sensitivity analysis for aerodynamics and stealth is first carried out, respectively, by finite difference method for hierarchical parameters in order to classify the generalized parameters. Then, in the second round, sensitivity analysis is carried out based on the optimal fitness to obtain three levels of design parameters. According to the sensitivity analysis results in practical operation, the criterion for sensitivity analysis of individual disciplinary and optimal fitness is set as the sensitivity of the parameters is larger than 1. The relatively independent sensitive analysis of hierarchical parameters can reserve the progressive of parametric modeling, and the resultant three-level parameters will be more suitable for hierarchical progressive optimization and get better optimization efficiency.

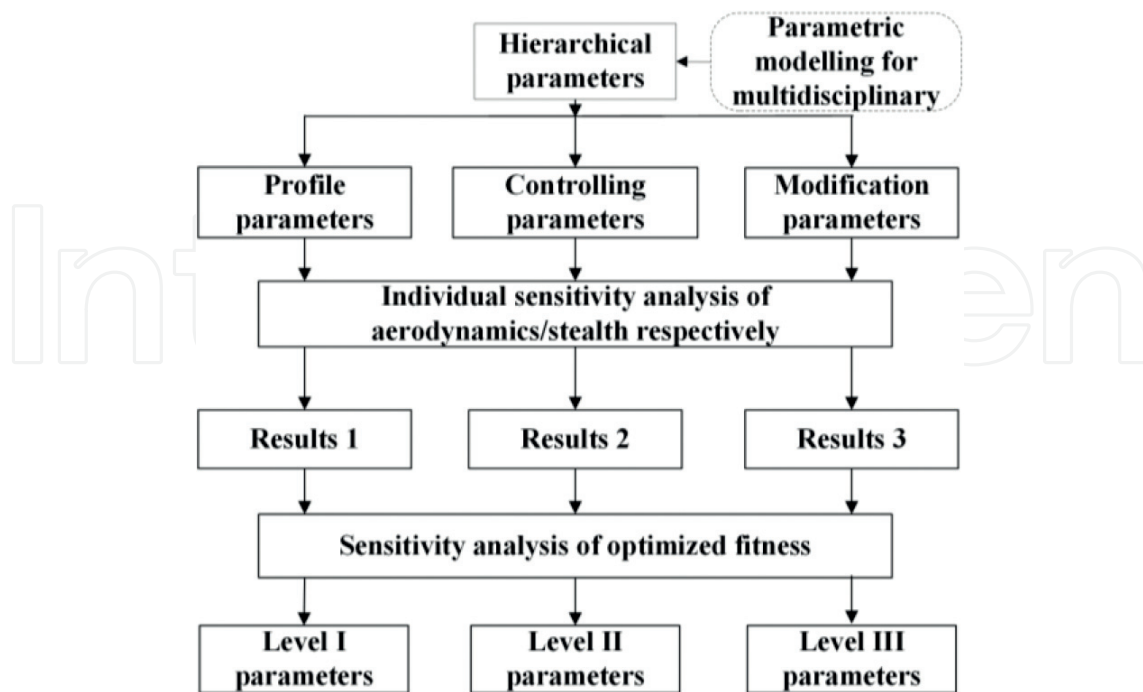


Figure 5. Hierarchical progressive optimization based on sensitivity analysis.

5. Analysis and discussion

5.1. Optimization descriptions

The aerodynamic/stealth optimization design is conducted for four-tailed layout aircraft, which can be described as follows:

1. Calculation conditions: flight height of 5 km, Mach number of 0.7, radar microwave frequency of 6.0 GHz and threat angle of 0~120°.
2. Constraint conditions: radar cross section (RCS) in the opposite direction no more than 0.01 and the cross section area of fuselage no more than 0.5 m².
3. Objective function: the maximum lift-to-drag ratio with the weight of 0.5, minimum RCS in the forward direction with the weight of 0.5 and minimum RCS in side direction with the weight of 0.5.
4. Original design parameters: 131 modeling parameters.

As shown in **Figure 1**, the optimization process is started with parametric modeling for several disciplines and the corresponding computational grid. The two-round sensitivity analysis is then conducted to classify the hierarchical generalized parameters. The MDO is implemented by differential evolution method [6] and hierarchical progressive optimization. According to the preliminary test of multimodal function with the same number of design parameters, the control parameters are set for differential evolution method as the initial population is double of the number of design parameters, the number of optimization generations of each stage is 30, the scaling factor is 0.6, and crossover factor is 0.5.

5.2. Optimization results

The sensitivity analysis results are shown in **Table 2**. After two rounds of sensitivity analysis, the number of first-level design parameters is reduced by 39.9%, the number of second-level design parameters is reduced by 30%, the number of third-level design parameters is reduced by 80.9%, and the number of all design parameters is reduced by 64.4%.

The normalized optimization process is shown in **Figure 6**. It indicates that the hierarchical progressive approach with two-round sensitivity analysis has great advantages with better optimization efficiency according to the variations of fitness versus the evolution generations.

Parameter level	Numbers	First round	Second round	Variation
Level I	28	21	17	39.90%
Level II	20	16	14	30%
Level III	84	36	16	80.90%

Table 2. The variations in the number of design parameters.

Table 3 is the statistical table of optimization adaptive value. As for the initial fitness of 59.818, the optimization results show that hierarchical progressive optimization with two-round sensitivity analysis increases the adaptive value by 51.1%. The objective function in two-round sensitivity analysis is shown in **Table 4**. It can be seen that the lift-to-drag ratio is increased by 38.5%, RCS in the forward direction is reduced by 52.03%, and RCS in side direction is reduced by 62.8%. **Figure 7** shows the aircraft configuration before and after the optimization. The

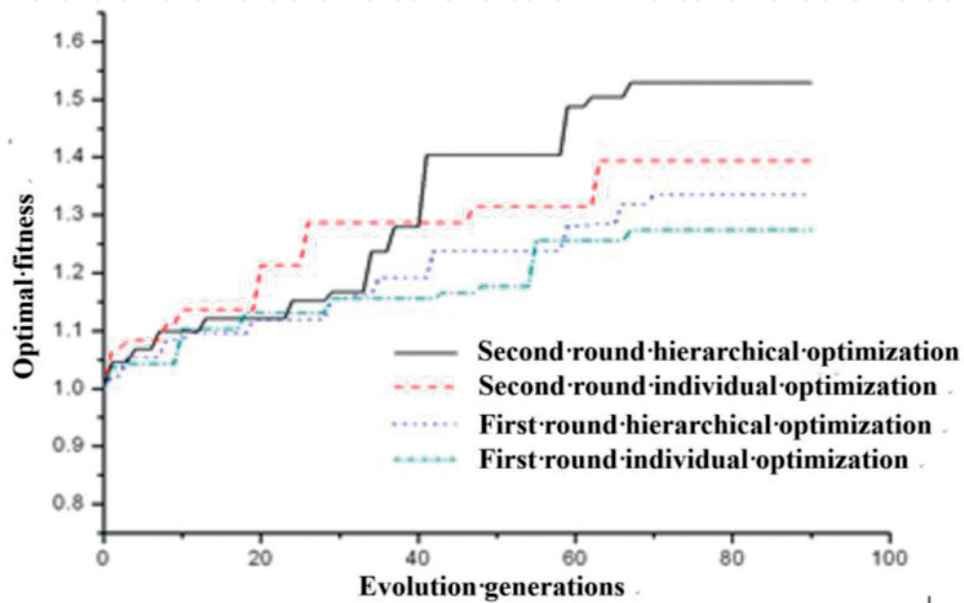


Figure 6. The variation of optimal fitness versus evolution generations.

Optimization process	Optimal fitness	Variation
Second round hierarchical optimization	90.385	51.1%
Second round individual optimization	83.41	39.44%
First round hierarchical optimization	79.91	33.59%
First round individual optimization	76.186	27.36%

Table 3. The variation of optimal fitness.

Optimal objects	Initial value	First round optimization	Second round optimization	Second round optimization	Variation
Lift-to-drag ratio	4.21	4.98	5.32	5.83	+38.5%
RCS in forward direction	0.0123	0.0086	0.0072	0.0059	-52.03%
RCS in side direction	1.6786	1.2658	0.8963	0.6237	-62.8%

Table 4. The variation of optimal objects.

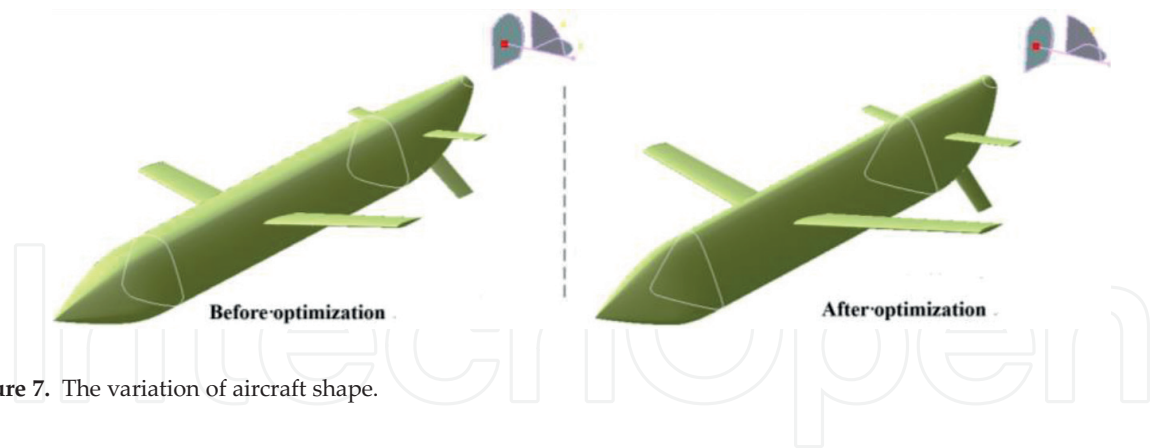


Figure 7. The variation of aircraft shape.

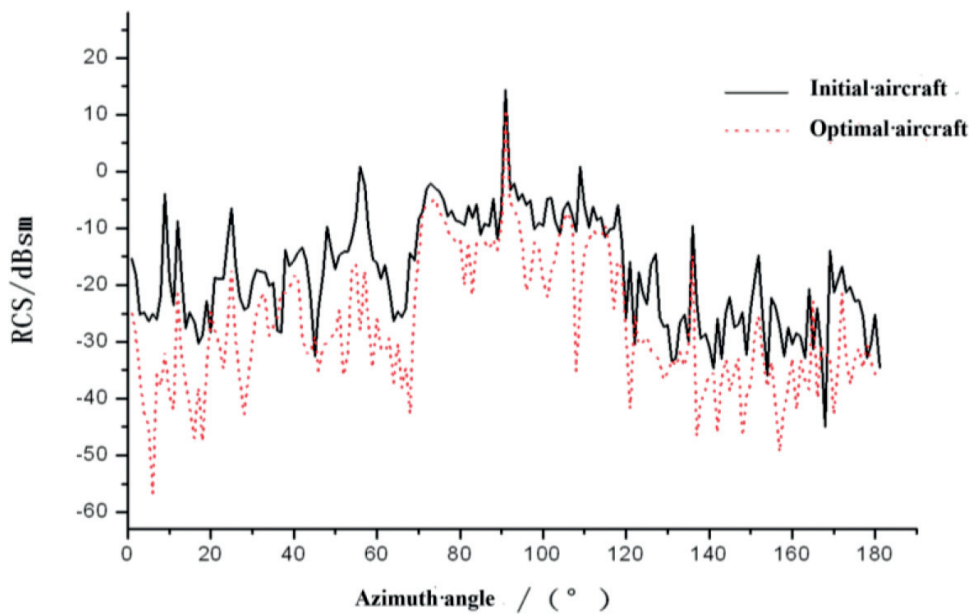


Figure 8. The variation of RCS value.

cross section of fuselage is significantly altered from quasi-quadrangle to quasi-triangle, which meets the requirements of stealth, while the aspect ratio and area of the wing are both increased. RCS in the opposite direction is 0.0055, and the fuselage cross section is 0.396 m². **Figure 8** shows the comparison between RCS before and after optimization. The RCS value is significantly reduced, which means the stealth performance is better after optimization.

6. Conclusions

The optimization results indicate that hierarchical progressive optimization based on generalized parametric modeling and sensitivity analysis demonstrates high optimization efficiency and excellent optimization results. Within the prerequisite of optimization constraints, the lift-to-drag ratio is increased by 38.5% and RCS decreases by more than 50%, which achieve the goal of multidisciplinary optimization design.

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