# AERODYNAMIC CONFIGURATION DESIGN OF AIRCRAFT USING MULTI-OBJECTIVE GENETIC ALGORITHM

**Wang Xiao-peng, Gao Zheng-hong**
**Department of Aircraft Engineering**
**Northwestern Polytechnical University**
**Xi'an, 710072, P.R.China**

## Abstract

*A numerical procedure for the aerodynamic configuration design of aircraft based on genetic algorithms, with single-point, multi-point and multi-objective optimization capabilities, is presented. Optimization process is executed based on a light fighter, which is composed of wing, body and horizontal tail. The geometry and relative position of three parts, wing, body and horizontal tail, are chosen as the design variables. The objective is to acquire the maximum lift-to-drag ratio under the given constraints.*

*Three single-point designs in the subsonic, transonic and supersonic region have been first addressed. Then multi-point designs are taken under transonic and supersonic cases with three different weighted factors. Lastly, the pareto front of optimization design is obtained using multi-objective pareto genetic algorithms, and the designed results are shown under the same design condition as multi-point. A comparison between the results obtained in three ways is established, showing the effectiveness of multi-objective optimization used to deal with aerodynamic configuration design.*

## 1 Introduction

In recent years, aerodynamic optimization designs by means of numerical optimization methods have been receiving more attention. Through use of numerical methods both design period and cost could be considerably reduced. Advantages of high efficiency and low cost of numerical methods have been verified via plenty of practical designs.

As the development of computation technology and computational fluid dynamics, research on optimization and design of aeronautic and astronautic vehicles have got great achievement. Most of them have been concentrated on design of airfoil and wing[1-5], only a minority of them is taken on aerodynamic configuration of a whole aircraft[5]. Moreover, plenty of work has been limited to single-objective optimization, investigations on multi-objective optimization are far away from suffice.

Aircraft design is a systemic engineering with high complexity. It comes down to aerodynamic configuration, structural layout, and electronic facility, control system and other mission-related equipment. Generally, aircraft design problems fall into categories of multi-disciplinary design[6]. Even considering the aircraft design problems from a purely aerodynamic point of view, requirements from different design points are to be taken into account to guarantee at least acceptable off-design performance. Therefore, successful design methods should have multi-point design capabilities.

Nowadays, nearly all of the optimization methods can be sorted into determinate and stochastic methods. Determinate methods have the common property that a determinate search direction is followed. Of the determinate optimization methods, probably the most common-used design method is gradient-based optimization. This process involves computing the sensitivity derivatives of the objective function with respect to the design variables, estimating the design changes that will lead to improvement, and making the changes and reevaluating the new design. Therefore, the optimization result is greatly related to the property of objective function as well as design variables.

Another category of design methods considered are general search methods which belong to stochastic methods, such as genetic algorithms, simulated annealing methods and Monte-Carlo methods. These methods are robust since only the value of objective function, but not its gradients with respect to the design variables, is required. However, the major drawback of these methods is that they usually require thousands of analysis runs to search the design space for even fairly simple cases.

The optimization results depend greatly on three aspects: selection and representation of design variables, property and efficiency of numerical optimization method, and accuracy and efficiency of aerodynamic analysis method. Therefore, it is important that one reliable and efficient aerodynamic analysis method should be chosen if numerical optimization method has been determined.

Aerodynamic analysis by making use of Euler or Navier-Stokes equations solver will bring great cost of both computer CPU time and memory, in spite of rapid development of computational fluid dynamics and technology of computer today. If genetic algorithm is employed as optimization tool in aerodynamic optimization, combining with aerodynamic analysis by Euler equations solver or Navier-Stokes equations solver, the computation cost will increase to an egregious extent. In other words, it is unpractical to design complex configuration of a whole aircraft by adopting this strategy. With regard to this situation, simple aerodynamic analysis approach has to be chosen to reduce the computation cost for making sure the proceeding of optimization.

In this paper, a simple engineering tool for evaluating aerodynamic forces of a whole aircraft with conventional configuration is introduced here. First of all, this method is verified through comparison between computational results and experimental results for a given aircraft. Then, the process of aerodynamic configuration optimization and design are carried out using single-point, multi-point and multi-objective strategies in order.

## 2. Optimization method

Just as stated above, the genetic algorithms are global search approach dealing with optimization problem by simulating the evolution of natural creature on the genetic principle of natural selection and survival. Compared with the conventional determinant methods, genetic algorithms are perfectly robust, global and transplantable. Furthermore, when genetic algorithms are used in optimization problems, only values of objective functions of individual are required, and no requirement for continuity and derivative of functions as well as calculation of gradients of objective functions. Just for the great advantages, genetic algorithms have been widely used in engineering optimization.

### 2.1 Genetic algorithm for single objective optimization

Simple genetic algorithm (SGA)[7] is a typical scheme among the genetic algorithms. SGA implements the evolution of population through the operations of reproduction, crossover and mutation based on binary encoding and decoding. Reproduction is the genetic process that make the better genes of ancestor are inherited by their offspring by greater probability by roulette wheel selection. The process of crossover produces new individual in the offspring by randomly exchange some genes in chromosomes of two individuals selected from parents. Mutation changes some genes of chromosomes of selected individual. It can be concluded that crossover and mutation produce new individual in the offspring and reproduction makes better character of parents appear in offspring, their common action make species of creature evolve based on inheritance.

Although SGA is easy to be understood and turned into program code, it has some disadvantages such as higher computation cost for binary encoding and decoding. Moreover, Hamming cliff may appear during the search for optimum. For resolving these shortcomings existed in SGA, real number could be used to encode and so decoding is not needed any more. Furthermore, genetic algorithms based real number skill may have higher efficiency than those based on binary skill [8].

In this work, a sort of extension of the elitism strategy is introduced into algorithm, and ranking selection is employed to prevent evolution from premature convergence or stagnation[8]. Moreover, adaptive evolutionary recombination is taken as recombination part, and non-consistent mutation strategy is adopted here as mutation part.

Since most optimization problems are constrained, it is important to deal with the constraints properly. Here, dynamic punishment[9] is used to make sure that the constraints are satisfied. Dynamic punishment will eliminate those designs violated some of the given constraints, and it is possible to search on a wider design space at the beginning of evolution and satisfy the constraints at the end of evolution.

## 2.2 Pareto genetic algorithm for multi-objective optimization

The mostly common approach of dealing with multi-objective problems is through weighted linear combination of the different objectives. In this way, multi-objective problems could be converted into single-objective problems by combining multiple objectives into single one. The drawback of this approach lies at that the solution of problem, to some extent, depends on the choice of the relative weights assigned to every objective. Sometimes, it is difficult to make decision about how to interrelate them properly, specially when multidisciplinary optimization problems are faced.

One of the ideal schemes may be addressed as followed. It can be convenient to acquire all possible solutions, which are members of the optimal solution set according to different inclination for designed results, and then final design can be selected from that set. To implement this idea, the notions of domination and pareto optimal solution are introduced.

Let $F = (f_1, \ldots, f_n)$ be the objective vector of a maximization problem with $n$ objectives, and $F^a, F^b$ be two candidates, then $F^a$ dominates $F^b$ if for any $i \in \{1, \ldots, n\}$ such that $F_i^a \geq F_i^b$, and there is an objective such that $F_i^a \succ F_i^b$.

All of the non-dominated solutions constitute the pareto front, which is the set of pareto optimal solutions. It is clear that no design points with better performance are possible to exist in the set of possible solutions. In the pareto front, every design point has better performance at some aspects but worse performance at other aspects. In other words, if a solution belongs to the pareto front it is not possible to improve one of the objectives without deteriorating some of the others.

Different from some conventional optimization methods, genetic algorithms are capable of dealing with multi-objective design problems in a more straightforward way. With continuation of genetic evolution, design points with better performance may be inserted the pareto front, and those with inferior performance will be eliminated from the pareto front. Thus, a whole set of pareto optimal solutions, which are composed of all possible alternative solutions to the problem, meeting the requirements at different levels of compromise, can be developed.

Due to the difference between pareto genetic algorithm and single-objective genetic algorithm, some disposal adopted in single-objective genetic algorithm cannot be transplanted to pareto genetic algorithm directly. To compare two solutions, population ranking is introduced here. The main idea of population ranking is that all solutions are classified into two ranks, rank one is for the pareto optimal solutions, others belong to the second rank. Furthermore, in order to prevent solutions in the pareto front from justling, pareto solution filter is designed. If the distance between two pareto solutions is smaller than the assigned limit value, then one solution is eliminated from the pareto front.

Except two skills presented above, the other treatments used for single-objective optimization design are employed here.

## 3. Aerodynamic analysis method

AERO3D, developed by aircraft design research group of NPU based on Axelson's evaluation theory[10,11], is used to carry out aerodynamic analysis of aircraft. This approach has the capability of evaluating aerodynamic forces on aircraft with/without horizontal tail. The comparisons between the computational results and experimental results on aerodynamic properties are shown in fig1-.3. It can be concluded that the computational results accord well with the experimental results at lower angle of attack under 6 degree in spite of departure appeared at higher angle of attack.

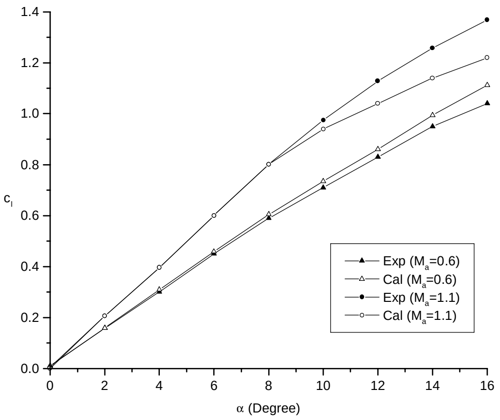


**Fig. 1 Comparison of lift properties between computational and experimental results**

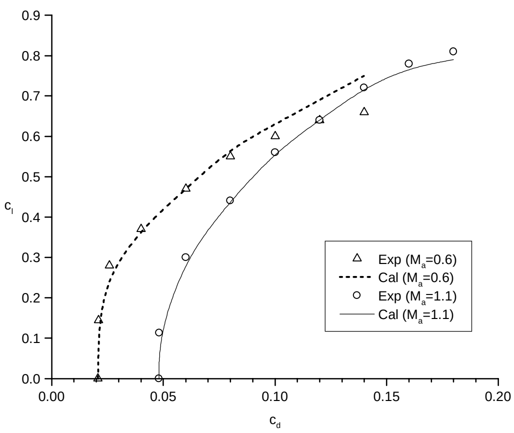


**Fig. 2 Comparison of lift-drag properties between computational and experimental results**

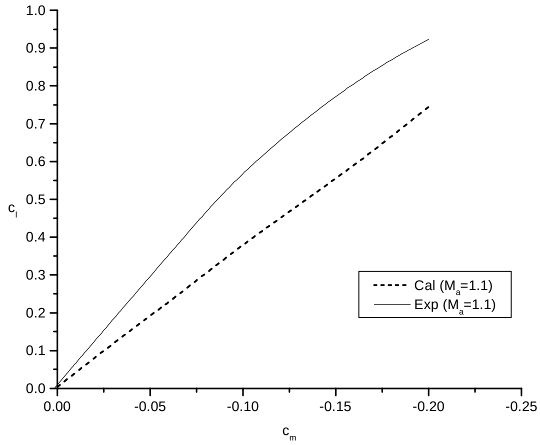


**Fig. 3 Comparison of pitching moment-lift property between computational and experimental results**

Since the investigation dealt with is only for the cases at low angle of attack, it is acceptable that this aerodynamic evaluation method is used to carry out aerodynamic analysis of aircraft at preliminary design stage.

## 4. Aerodynamic configuration optimization and design of aircraft

Three parts are followed in this work. They are:

a. Single-point designs
b. Multi-point designs through weighted combination
c. Multi-objective designs through pareto solutions.

The objectives of designs are to improve the lift-to-drag of aircraft with a conventional configuration.

Design variables of the optimization are totally 14, which are related to three parts: wing, body and horizontal tail. Four control parameters, aspect ratio, taper ratio, wingspan and sweep angle at the leading edge, which determine the planform of wing, are chosen as the design variables relevant to wing, provided that the profile of wing keeps constant. Three control parameters, length of body, length of nose and maximum diameter of cross section, are taken into consideration for optimization as design variables relevant to body of aircraft. For the horizontal tail more design variables are included here, they are area of surface, aspect ratio, sweep angle of tail and longitudinal station, vertical station and incidence of tail relative to body. The 14th design variable is longitudinal position of wing relative to body. All the control parameters can determine a feasible configuration of aircraft with conventional layout, under the help of design experience that has been accumulated for a long time.

Since the objective of this work is inclined to design a light combat fighter with less weight, the search space is limit to a small range containing an existed fighter which is chosen as the baseline of optimization. The ranges of design variables for configuration of aircraft are listed in table.1.

| Design Variables | Range |
|---|---|
| Aspect ratio of wing | [2.5,4] |
| Taper ratio of wing | [0.075,0.5] |
| Wing span(m) | [7,9] |
| Sweep angle of wing(L.E) (°) | [30,60] |
| Maximum diameter of body(m) | [1.1,1.2] |
| Nose length(m) | [4,8] |
| Length of body(m) | [10.5,12.5] |
| Aspect ratio of tail | [2,4] |
| Area of tail($m^2$) | [5,7] |
| Tail incidence(°) | [-5,5] |
| Sweep angle of tail(Q.L) (°) | [30,60] |
| Vertical height of tail(m) | [-0.01,0.01] |
| Longitudinal position of tail(m) | [8,10] |
| Longitudinal position of wing(m) | [5,7] |

**Table.1 Range of design variables**

To ensure the configuration to be designed is practical, some constraints must be given. The constraints include mainly the following aspects:

1.geometric constraints

For example, intersection is not allowed to occur between wing and horizontal tail, and wing should locate in front of the tail. Except for constraints considered above, area of wing is limited between $23m^2$ and $25m^2$ in the optimization.

2.aerodynamic constraints

To provide enough lift for flight of aircraft, minimum lift limit must be set. Moreover, trim state is considered in the design.

3.structural constraints

The configuration of aircraft should be realizable or enforceable, that requires structural considerations. For instance, length of wing at the root and cross section of body cannot be too small. It is noticeable that most of these considerations are in connection with geometric constraints.

The disposal of constraints can be classified into two categories. The first category contains the design variables restricted directly by the low and up bounds, the other in this paper, deals with that introduced from penalty functions to the value of the fitness. When constraints are violated, the fitness of this individual will be considerably decreased. In this way, designs violated some constraints will be excluded from design space and all constraints will be satisfied.

## 4.1 Single-point design

Initially, three different single-point designs have been carried out at Mach number (flight height) of 0.3(5km), 0.8(11km) and 1.4(15km) respectively, corresponding to subsonic, transonic and supersonic design states. The algorithm presented in section 2.1 is used. The lift-to-drag ratio when tail deflects for trim is directly taken as fitness value. Probability of recombination, reproduction and mutation are set to be 0.9, 0.1 and 0.01 respectively. Population size is taken as 100, and maximum evolution generation is taken as 60.

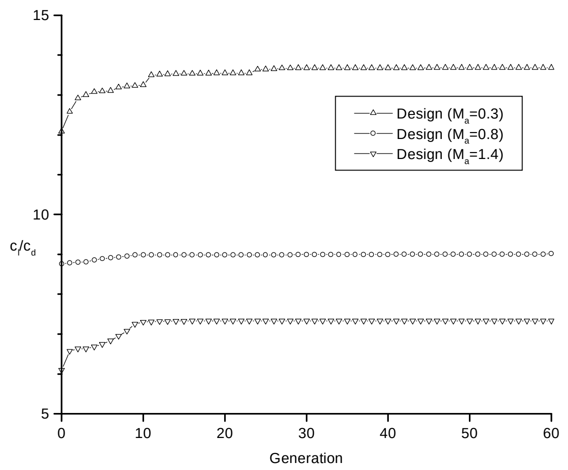


**Fig.4 Evolutionary histories of lift-to-drag ratio for single-point designs**

The optimal results are given in fig.4-6. Fig.4 shows the evolutionary histories of lift-to-drag ratio. Obviously the optimization results are improved as proceeding of evolution. Design variables corresponding to final results are listed in table.2. Comparison among performances of three designs and baseline is shown in fig.5. As anticipated, single-point designs are characterized by a deterioration of the performances at off-design conditions.

| Design Variables | M=0.3 H=5km | M=0.8 H=11km | M=1.4 H=15km |
|---|---|---|---|
| Aspect ratio of wing | 3.37 | 3.39 | 3.43 |
| Taper ratio of wing | 0.122 | 0.086 | 0.084 |
| Wing span(m) | 8.90 | 8.86 | 8.91 |
| Sweep angle of wing(L.E) (°) | 30.74 | 35.33 | 45.31 |
| Maximum diameter of body(m) | 1.166 | 1.172 | 1.198 |
| Nose length(m) | 4.401 | 7.881 | 4.008 |
| Length of body(m) | 10.592 | 11.358 | 11.22 |
| Aspect ratio of tail | 3.914 | 3.971 | 3.76 |
| Area of tail($m^2$) | 6.9 | 6.7 | 6.7 |
| Tail incidence(°) | -0.83 | 1.92 | -0.03 |
| Sweep angle of tail(Q.L) (°) | 32.38 | 36.22 | 46.51 |
| Vertical height of tail(m) | 0.007 | 0.009 | -0.003 |
| Longitudinal position of tail(m) | 8.89 | 9.54 | 9.11 |
| Longitudinal position of wing(m) | 5.3 | 5.94 | 6.04 |

**Table.2 Results for single-point designs in subsonic, transonic and supersonic regime.**

Furthermore, performance at subsonic case is better no matter where the design points are located. With this understanding, it provides us some information that subsonic regime may be not taken into consideration when multi-point and multi-objective designs are carried out.

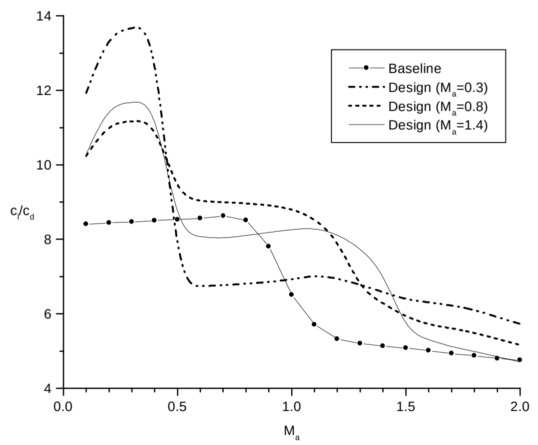


**Fig.5 Comparison among performances for single-point designs**

The final designed configurations are shown in fig.6, from which we can get some information about configuration of lighter aircraft. With increase of flight velocity of aircraft, body should be slenderer and sweep angle of wing should be greater if higher lift-to-drag ratio is required.

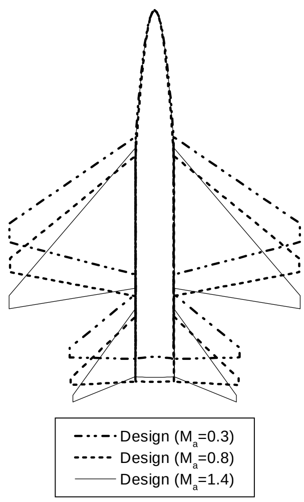


**Fig.6 The final configurations for single-point designs**

## 4.2 Multi-point design

Since single-point designs generally lead to unacceptable off-design performance, it is necessary to specify multiple design points. In this part, three two-point designs are carried out at Mach number of 0.8 and 1.4 and the flight height of 13km, corresponding to transonic and supersonic cruise conditions. Here, the objective functions are computed as a weighted sum of lift-to-drag ratio:

$$obj = \alpha(c_l / c_d)_1 + (1-\alpha)(c_l / c_d)_2$$

Where subscript 1 and 2 mark transonic and supersonic states, respectively. Three different runs have been carried out with $\alpha$ of 0.3, 0.5 and 0.7, respectively. The same control parameters for genetic algorithm are used as those in single-point designs.

The design results obtained corresponding to the final results are listed in table.3, and comparison among the performances of three designs and baseline is shown in fig.7. It can be seen that inclination for design point at Mach number of 0.8 will make design result approach that at the same design point for single point, and depart from the other design point. When $\alpha$ is equal to 0.7, the performance of the design result is the best for Mach number of 0.8 among the three designs, and if $\alpha$ is set to 0.3 result for 1.4 is the best one. From the results, subsonic performance at all the flight speed range is acceptable. The final optimal configurations are shown in fig.8.

| Design Variables | $\alpha$ =0.3 | $\alpha$ =0.5 | $\alpha$ =0.7 |
|---|---|---|---|
| Aspect ratio of wing | 3.29 | 3.33 | 3.39 |
| Taper ratio of wing | 0.174 | 0.088 | 0.086 |
| Wing span(m) | 8.74 | 8.76 | 8.87 |
| Sweep angle of wing(L.E) (°) | 30.35 | 31.28 | 30.63 |
| Maximum diameter of body(m) | 1.123 | 1.119 | 1.195 |
| Nose length(m) | 4.101 | 5.598 | 5.244 |
| Length of body(m) | 10.804 | 11.155 | 11.268 |
| Aspect ratio of tail | 3.938 | 3.865 | 3.93 |
| Area of tail($m^2$) | 6.9 | 6.7 | 6.7 |
| Tail incidence(°) | 2.0 | 1.92 | 1.78 |
| Sweep angle of tail(Q.L) (°) | 30.38 | 32.96 | 32.37 |
| Vertical height of tail(m) | 0.008 | -0.001 | -0.001 |
| Longitudinal position of tail(m) | 9.11 | 9.39 | 9.52 |
| Longitudinal position of wing(m) | 5.58 | 5.75 | 5.88 |

**Table.3 Results for multi-point designs in subsonic, transonic and supersonic regime.**

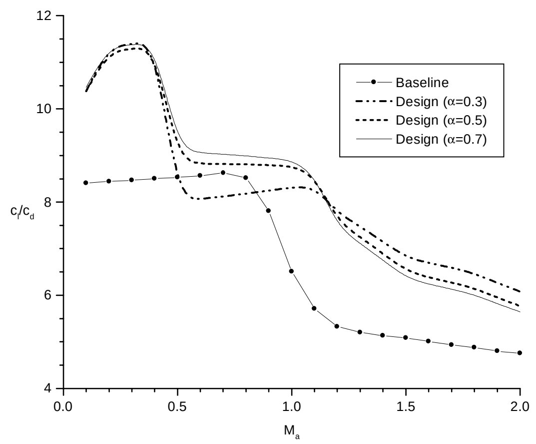


**Fig.7 Comparison among performances for multi-point designs**

From the results, we will understand that different inclination may induce different design result, which makes off-design performance vary to a great extent. And we can know that the solution is largely dependent on the values of the weights used in the objective function, that means that the assignment of weights has great influence on the design results, while the proper choice of weights rely largely on the experience of the designer.

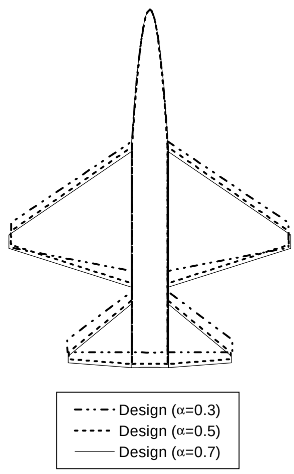


**Fig.8 The final configurations for multi-point designs**

## 4.3 Multi-objective design

Lastly, two-point designs by means of pareto genetic algorithm are taken at the same design points, with Mach number of 0.8 and 1.4 and the flight height of 13km. Different from the representation of objective function in section 4.2, objective functions in multi-objective design are computed directly as two lift-to-drag ratios at two design points. Algorithm described in section 2.2 is used in multi-objective design. The control parameters for genetic algorithm are kept the same as those in single-point designs.

Pareto front is obtained as shown in fig.9. Three designed results, Design-A, Design-B, Design-C, are marked in fig.9, and their corresponding performances and configurations are shown in fig.10 and fig.11. The design results obtained corresponding to final results are listed in table.4.

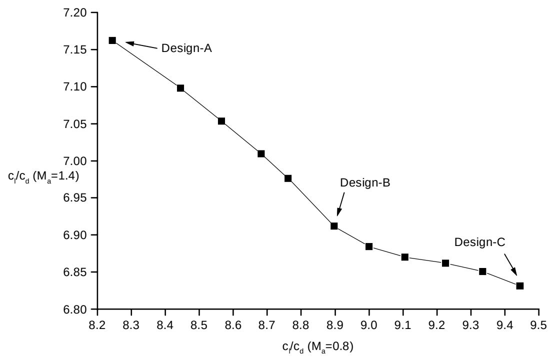


**Fig.9 Pareto front for multi-objective designs**

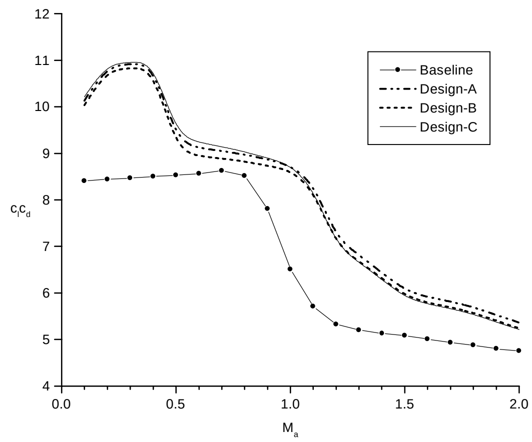


**Fig.10 Comparison among performances for multi-objective designs**

Different from multi-point designs, multi-objective designs by means of pareto genetic algorithm provide designers much more choices through pareto front. When designs move attention from one side to another side on the front, inclination is increasing for one objective and decreasing for the other. In this way, designer may get a series of design results with different requirements. Furthermore, from fig.7 and fig.10 it is obvious that multi-point designs may lead to deterioration of the performances at off-design conditions because of inappropriate assignment of weights, however, it is impossible to occur for multi-objective optimization by means of pareto strategy.

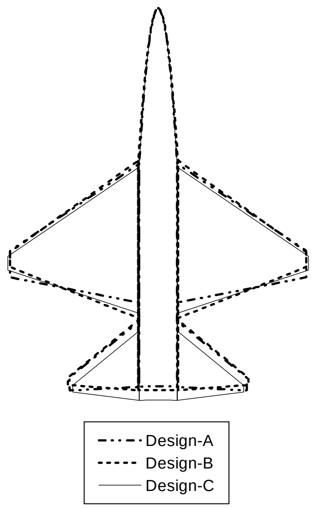


**Fig.11 Comparison among performances for multi-objective designs**

| Design Variables | A | B | C |
|---|---|---|---|
| Aspect ratio of wing | 3.29 | 3.08 | 3.39 |
| Taper ratio of wing | 0.174 | 0.085 | 0.084 |
| Wing span(m) | 8.74 | 8.74 | 8.87 |
| Sweep angle of wing(L.E) (°) | 30.35 | 31.59 | 30.63 |
| Maximum diameter of body(m) | 1.123 | 1.172 | 1.119 |
| Nose length(m) | 5.394 | 7.881 | 5.598 |
| Length of body(m) | 11.123 | 11.24 | 11.528 |
| Aspect ratio of tail | 3.979 | 3.971 | 3.765 |
| Area of tail($m^2$) | 6.9 | 7.1 | 6.7 |
| Tail incidence(°) | 1.92 | 1.71 | 1.99 |
| Sweep angle of tail(Q.L) (°) | 32.14 | 32.42 | 32.37 |
| Vertical height of tail(m) | 0.001 | 0.009 | 0.008 |
| Longitudinal position of tail(m) | 9.43 | 9.39 | 9.76 |
| Longitudinal position of wing(m) | 6.01 | 5.97 | 6.10 |

**Table.4 Results for multi-objective designs in subsonic, transonic and supersonic regime.**

## 5. Conclusions

Aerodynamic configuration designs for improving an existed light fighter have been obtained, by means of numerical optimization procedure through combination of genetic algorithms with aerodynamic analysis tool. Objective of optimization is to increase lift-to-drag ratio of aircraft, considering transonic and supersonic cruise states at relevant flight heights. Optimized configurations are satisfactory for satisfying the given constraints.

It can be concluded that genetic algorithm is capable of dealing with single-point, multi-point and multi-objective problems, and that AERO3D is effective for aerodynamic analysis at the preliminary design stage. Furthermore, when pareto genetic algorithm is used to deal with optimization problem with multiple objectives, more flexibility may be provided according to designer's inclination or actual requirements for design.

## References

[1] S Eyi and K D Lee. Inverse airfoil design using the Navier-Stokes equations. AIAA paper 93-0972. 1993

[2] R M Greenman, S Cheung and E L Tu. Coupled Navier-Stokes and optimizer analysis of a transonic wing. *Journal of Aircraft*, vol. 35, No. 3, pp 362-371, 1998.

[3] B Eric, S Adeline, B Erwan, G Nicolas and C Tuncer. Two-dimensional aircraft high lift system design and optimization. AIAA paper 98-0123. 1998

[4] A Jameson, N A Pierce and L Martinelli. Optimum aerodynamic design using the Navier-Stokes equations. AIAA paper 97-0101. 1997

[5] R L Campbell. Efficient viscous design of realistic aircraft configurations. AIAA paper 98-2539. 1998

[6] J Dudley, X Huang, P E Macmillin, B Grossman, R Haftka, W H Mason. Multidisciplinary optimization of the high-speed civil transport. AIAA paper 95-0124. 1995.

[7] Goldberg J H. *Genetic algorithms in search, optimization and machine learning*. Addison-Wesely. Reading MA, 1989.

[8] Michalewicz Z. *Genetic algorithms + data structures =evolution progress*. Springer-verlag, Berlin, 1992.

[9] Joines J and Houck C. On the use of non-stationary penalty functions to solve nonlinear constrained optimization problems with GAs. *Proc. of the 1st IEEE Int'1. Conf. on evolutionary computation (ICEC'94).* Orlando, Florida, USA. IEEE press. pp579-584, 1994

[10] J A Axelson. Estimation of transonic aircraft aerodynamics to high angle of attack. AIAA paper 75-996. 1975

[11] J A Axelson. Estimation of transonic aircraft aerodynamics to high angle of attack. *Journal of Aircraft*, vol.14, No.6, 1977.