

AIRCRAFT PRELIMINARY DESIGN: GENETIC ALGORITHM BASED OPTIMIZATION METHOD

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Abstract

Multidisciplinary Design Optimization is recognized as the most promising approach to aircraft design.

Aircraft preliminary design is a crucial phase for the development of an air vehicle design. The definition of “the best aircraft design” is quite a difficult task since a large number of design variables have to be combined together in order to maximize the objective function under several constraints. The definition of the objective function itself is demanding, as it is a trade-off among several performances that shall be maximized.

This paper shows the design and development of a Genetic Algorithm based optimization method applied to the preliminary design of an aircraft: the presented case study considers Breguet equation for range optimization.

The traditional approach to aircraft preliminary design reduces the number of design variables based on statistical data obtained by previous design knowledge. Within the current scenario, the use of evolutionary algorithms is more significant than in the past, as opposed to direct search methods such as grid searching, random searches, nonlinear simplex and gradient methods.

1 Introduction

Aircraft conceptual design is a very complex and iterative problem, that involves a huge amount of variables and constraints, merged in a multidisciplinary approach. The definition of the “best” configuration for a new aircraft is an high iterative process starting with

requirements and constraints definition, and ending with the optimum values of a set of design variables. Since several disciplines are involved, it is often difficult to foresee the design effects due to a variable change on the whole project. In this context, advanced methods and tools for multi-disciplinary analysis have been developed for aircraft preliminary design.

In particular, we focused on Genetic Algorithms as a robust tool for optimization problems; several studies dealing with Genetic Algorithms have been developed in almost all sciences fields, since they can easily manage several variables, within different disciplinary domains. In this context the aim of this work is to explore the possibility to introduce such methods in aircraft preliminary design processes, in order to define the “best” design configuration, in relation to design goals and constraints. A Genetic Algorithm has been introduced, with the objective of maximizing the aircraft range and a case study referring to a regional configuration has been finally tested.

1.1 Evolutionary tools for Aircraft Preliminary Design

Advanced analysis methods and parametric sizing codes have been widely used in several studies where many design variables are present and governed by multidisciplinary relations, under several constraints and requirements. In particular, the aeronautical design is driven by multidisciplinary optimization problems and aircraft preliminary design suits to evolutionary tools features. In spite of this, Genetic Algorithm optimization processes are not commonly used. Some interesting case studies

refer to the employment of Genetic Algorithms for aircraft configuration definition ([1]), others for aerodynamic surfaces definition ([2]), and others in rotorcraft design ([3]). In such analysis, the introduction of Genetic Algorithm tools in the design process allows to define a first tentative configuration, in an easier manner, to be developed in further design phases.

With reference to [4], the most promising case studies of evolutionary design in the aeronautical domain are low boom supersonic design, green aircraft design and non-planar wings design.

In [1] a design configuration is achieved by means of combining an high number of design variables, to identify the lightest feasible aircraft, in relation to a fixed payload and within some given performance requirements. The presented case study considers a medium range commercial aircraft, specifically, the Boeing 717 has been considered as a reference for performance requirements definition. The GA provides an higher number of changes in the design variable domains, in respect to conventional aircraft design procedures and more design solutions are analyzed at the same time. The reached best design solution saves the 5% of weight compared to reference aircraft configuration, with similar mission profile and payloads. Furthermore, results obtained by means of the GA optimization procedure are comparable to advanced configuration. Optimization results are shown in Figure 1.

Marta, 2003 [5] shows an example of preliminary aircraft design, by means of a GA tool. Wing, tail and fuselage geometry and design parameters are considered, together with thrust requirements and operating parameters, while the objective function aims to maximize the range. A regional jet has been considered as reference for constraints definition.

Buonanno and Mavris ([6]) focus on Genetic Algorithms as a support tool for concept selection: the decision making process is possible even without a sufficient awareness of variable impact on the whole system.

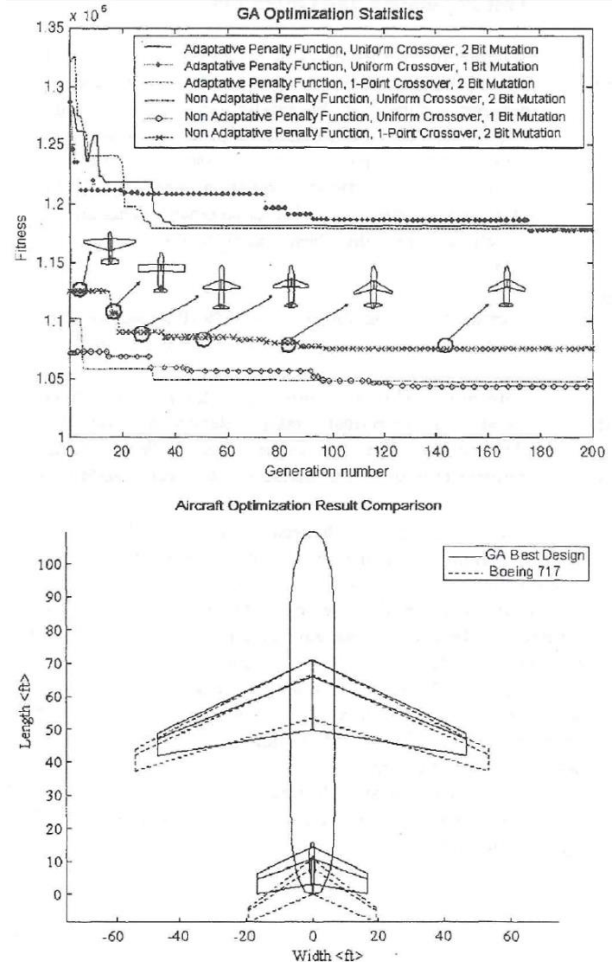


Figure 1 Aircraft Optimization results in [1]: GA convergence (on the top) and results comparison with reference configuration

The aim of their work is to develop a design methodology in order to define relationships between requirements and aircraft configurations; a small supersonic transport vehicle is considered as case study. An hybrid quantitative/qualitative Genetic Algorithm is conceived, in order to insert designer impressions in the optimization procedure.

An optimization tool was proposed in [7]: different algorithms were merged and applied to a general aircraft design. Weight estimation has been performed by an AHP (Analytical Hierarchy Process); iterations of GA and TOPIS-Fuzzy (Technique for Order of Preference by Similarity to Ideal Solution in Fuzzy environment) are used to identify the best solution.

2 Problem Modeling

The definition of “the best aircraft design” is quite a difficult task since a large number of design variables have to be combined together in order to maximize the objective function under several constraints.

The definition of the objective function itself is demanding, as it is a trade-off among several performances that shall be maximized.

The preliminary design process is based on aircraft components/group weight analysis that can be performed at many levels of detail. Different methods can be applied based either on approximate estimation or statistical one.

In this paper the preliminary design problem is modeled by means of group weight estimation based on both approximate methods and statistical equations obtained by regression analysis as described in [8].

Specifically, the following group weights are estimated: wing weight, fuselage weight, vertical tail weight, horizontal tail weight, engine weight and “all-else empty” weight. The first four terms are estimated based on statistical methods (Eq. 1, 2, 3, 4) while the remaining two terms are estimated by means of approximate methods (Eq. 5, 6). The variables in the following equations are reported in table A.1 in the appendix section.

$$W_{wing} = 0.051(W_{dg}N_z)^{0.557}S_w^{0.649}AR^{0.5}\left(\frac{t}{c}\right)_{wing}^{-0.4}(1+l)^{0.1}S_{csw}^{0.1} \quad (1)$$

$$W_{fuselage} = 0.3280K_{door}K_{LG}(W_{dg}N_z)^{0.5}L_f^{0.25}S_f^{0.302}\left(\frac{L_f}{D_f}\right)^{0.1} \quad (2)$$

$$W_{hor tail} = 0.0379\left(1 + \frac{F_w}{B_h}\right)^{-0.25}W_{dg}^{0.639}N_z^{0.1}S_{ht}^{0.75}L_t^{-1}K_y^{0.704}A_h^{0.166}\left(1 + \frac{S_e}{S_{ht}}\right)^{0.1} \quad (3)$$

$$W_{ver tail} = 0.0026\left(1 + \frac{H_t}{H_v}\right)^{0.225}W_{dg}^{0.556}N_z^{0.536}L_t^{-0.5}S_{vt}^{0.5}K_z^{0.875}A_v^{0.35}\left(\frac{t}{c}\right)_{vt}^{-0.5} \quad (4)$$

$$W_{propulsion} = 1.4 W_{en} \quad (5)$$

$$W_{else} = 0.17 W_{dg} \quad (6)$$

The design parameters are divided into sets: the independent design variables set V , the dependent design variables T and the set of constant parameters C .

$$V = (v_1; v_2; \dots; v_n) \quad (7)$$

$$T = (t_1; t_2; \dots; t_n) \quad (8)$$

$$C = (c_1; c_2; \dots; c_n) \quad (9)$$

Each design variable can vary in a range defined on the basis of the reference configuration and a set of constraints is applied to a subset of the dependent design variables.

2.1 Design Space Exploration: Genetic Algorithm

In this paper the design variables are explored and selected by means of a Genetic Algorithm tool, in order to maximize a range objective function. A fitness function has been developed on the basis of Breguet equation for range maximization, considering requirements and constraints for regional aircraft preliminary design.

The proposed Genetic Algorithm has been developed in Matlab (Mathworks Inc.) on the basis of a toolbox developed by [9] and adjusted for the aircraft configuration framework ([10]).

The algorithm is initialized by generating a first population of N (number of individuals) configurations. Each configuration is characterized by a chromosome randomly initialized on the basis of independent design variables, defined into their range of existence.

After the initialization procedure, the population is sorted according to decreasing values of fitness. Then, the evolution to the next population starts; this procedure is repeated until the algorithm reaches a point of convergence. After the definition of the first population, the evolution to the next one is carried out by dividing the previously sorted population into two parts, according to the generation gap parameter and to a stochastic sampling procedure: a random selection of the strongest individuals is performed in accordance to their fitness values. As higher is the fitness of an individual, as higher is the possibility that such chromosome is selected. Single-point crossover operators are considered in the presented case study; other re-combining functions could be applied, such as multi-point and shuffle crossover (Fig.2). Random Shuffle consists in a random exchange of the genes

composed by the two cuts of the chromosome, while single or double-point crossover changes the part of the first individual chromosome with the same part of the second individual from a random point to the chromosome end, or to another selected point (in case of double-point).

11.7928	75.6546	10.4014	0.6978	71.0050
11.5552	76.2295	8.0020	0.5275	80.8462

Initial Selected Chromosomes

11.7928	75.6546	10.4014	0.6978	80.8462
11.5552	76.2295	8.0020	0.5275	71.0050

Single Point Crossover

11.7928	76.2295	8.0020	0.6978	71.0050
11.5552	75.6546	10.4014	0.5275	80.8462

Double Point Crossover

11.7928	76.2295	8.0020	0.5275	80.8462
11.5552	75.6546	10.4014	0.6978	71.0050

Shuffle Crossover

Figure 2 Combining procedure between two initial chromosomes: example of single point, double point and shuffle crossover are reported

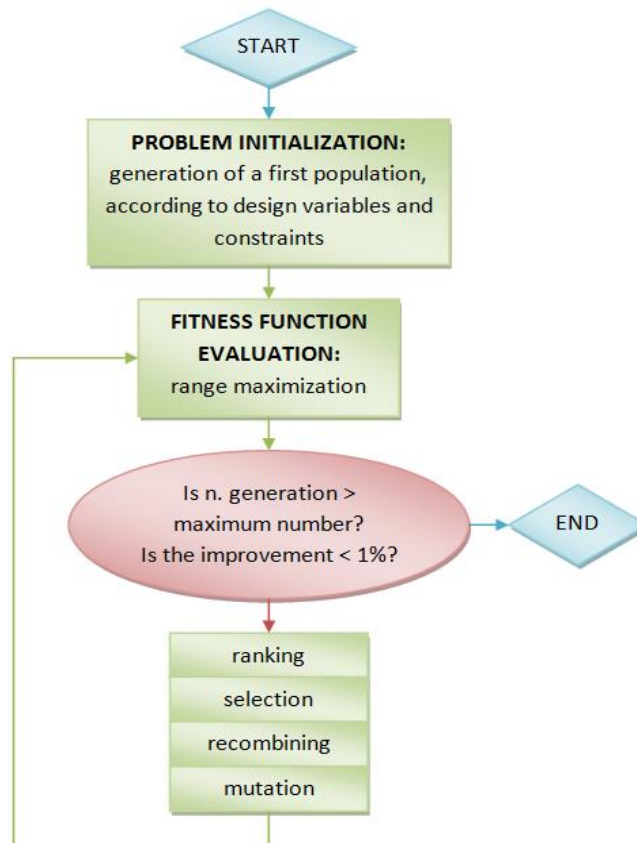


Figure 3 Genetic Algorithm flowchart

Chromosomes' structure is also evolved using mutation operators, in order to explore a wider variable space.

Crossover and mutation operators bring to the definition of offspring chromosomes, to be added to the first unchanged group. After such procedure the fitness function is evaluated and the process goes on till solution convergence. It could append that some chromosomes lead to not desired design solutions: in such cases the fitness function is forced to a low value, so that the not desired solution will be excluded. In the described example, passenger number and fuel weight have a lower and upper bound respectively.

The overall structure of the applied Genetic Algorithm is shown in Fig.3.

3 “Case Study” Description

A regional transport aircraft is considered as reference configuration for the case study described in this paper. Nevertheless, the described methodology and algorithm can be applied to any aircraft configuration. Main data for the reference configuration are reported in table 1.

Table 1. Reference configuration

	Variable	Value
L_f	Fuselage Length	70 ft
D_f	Fuselage Diameter	9.5 ft
B_w	Wing Span	80 ft
AR	Aspect Ratio	12
λ	Tapering Ratio	0.6
W_{fuel}	Fuel Weight	5500 lbs
N_p	Pax Number	48
R	Range	1754 km

3.1 Design Variables

The following parameters are identified as design variables for the optimization problem. Each design variable can vary in a range defined on the basis of the reference configuration.

Table 2. List of design variables

	Variable	min	max
L_f	Fuselage Length	60 ft	90 ft
D_f	Fuselage Diameter	8 ft	11 ft
B_w	Wing Span	70 ft	90 ft
AR	Aspect Ratio	11	13
λ	Tapering Ratio	0.5	0.7

The aircraft range is considered as the performance to be maximized. The optimization function is modeled on the basis of Breguet range equation (Eq. 10) where V represents the cruise speed, g the acceleration of gravity, SFC the thrust specific fuel consumption, $\frac{L}{D}$ the aircraft efficiency, W_i the initial weight and W_f the final weight.

$$R = \frac{V}{g \cdot SFC} \cdot \frac{L}{D} \cdot \ln \frac{W_i}{W_f} \quad (10)$$

The constraints are applied to a subset of the dependent design variables T as reported in table 2.

Table 3. List of constraints

	Variable	min	max
W_{fuel}	Fuel Weight	-	6000 lbs
N_p	Pax number	48	-

4 Results and discussions

The results are obtained by running the Genetic Algorithm in the conditions reported in table 4.

Table 4. Parameters for GA

	Parameter	value
N	Individuals number	300
MaxG	Max generations	100
GG	Generation gap	0.5

Those conditions are selected by means of a sensitivity analysis performed assigning different values to the GA parameters N_{ind} , $MaxG$ and GG . The GA set-up with the values reported in table 4 allow to obtain the most reliable results for the selected case-study.

Main data of the best configuration obtained by running ten times the GA for the selected case study are reports in table 5.

Table 5. Best configuration

	Variable	Value
L	Fuselage Length	60 ft
D	Fuselage Diameter	10.8 ft
Bw	Wing Span	82 ft
AR	Aspect Ratio	11.4
λ	Tapering Ratio	0.5
W_{fuel}	Fuel Weight	6755 lbs
N_p	Pax Number	48
R	Range	2120 km

As shown in Fig. 4, the best configuration is obtained after 61 generations. The algorithm converges in a solution having a range value lower than the one obtained for the best configuration. A comprehensive overview of the best configuration against the reference one is depicted in Figure 5.

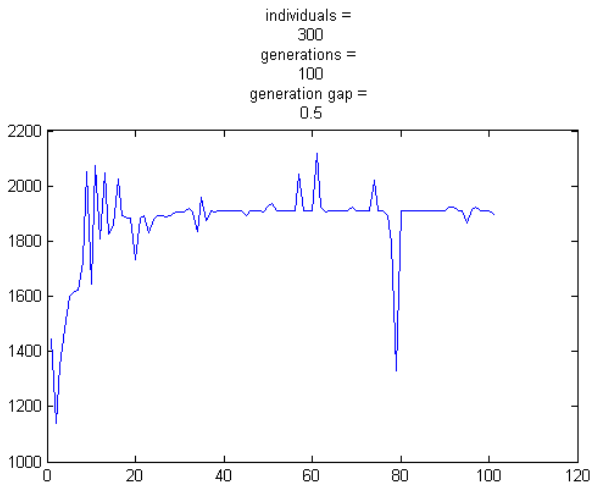


Figure 4. Fitness function vs. generations

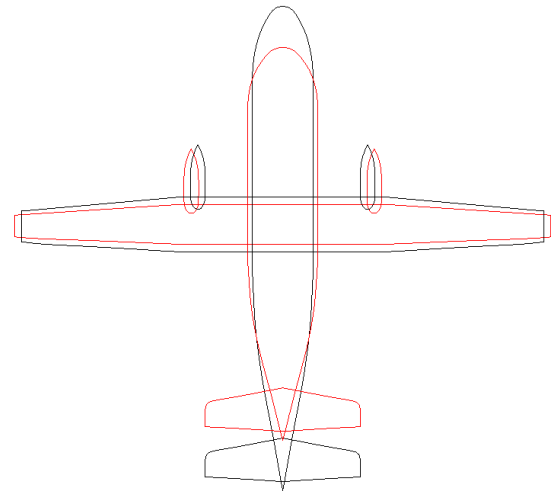


Figure 5. Top View of the reference configuration (in black) vs. the best configuration (in red)

Table 6 shows data for the configuration the algorithm converges in.

Table 6. GA convergence configuration

	Variable	Value
L	Fuselage Length	60 ft
D	Fuselage Diameter	10.8 ft
Bw	Wing Span	79 ft
AR	Aspect Ratio	11.6
λ	Tapering Ratio	0.5
W_{fuel}	Fuel Weight	6000 lbs
N_p	Pax Number	48
R	Range	1910 km

Conclusions

In this paper Genetic Algorithms are applied to a preliminary aircraft design study. The results obtained show how the implemented Genetic Algorithm outputs determine an improvement in the objective function. Specifically, the analyzed case study confirms that the use of evolutionary optimization algorithm is useful for evaluating the potential improvements that can be expected starting from an existing proven design. Such a tool may help the designer in determining whether stay in line with proven design or attempt to put in place more radical changes.

Further developments will include:

- refinement of the implemented Genetic Algorithm by improving the selection routines in order to ensure the convergence to the global optimal solution;
- enhancement of the model, to allow the analysis of more complex preliminary design problems.

References

- [1] Perez R.E., Chung J., Behdinan K., Aircraft conceptual design using genetic algorithm, 8th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, 6-8 September 2000, Long Beach, California, U.S.A.
- [2] Vicini A, Quagliarella D. *Inverse and Direct Airfoil Design Using a Multiobjective Genetic Algorithm*. AIAA Journal, Vol.35, n.9, pp1499-1505, 1997, doi: 10.2514/2.274.
- [3] Crossley WA, Laananen DH. *Conceptual design of helicopters via genetic algorithm*. Journal of aircraft. Vol.33, n.6, pp. 1062-1070, 1996, doi: 10.2514/3.47058.
- [4] Kroo I. *Aeronautica applications of evolutionary design*. VKI lecture series on optimization methods & tools for multicriteria/multidisciplinary design, 15-19 November, 2004.
- [5] Marta AC. *Parametric Study of a Genetic Algorithm using a Aircraft Design Optimization Problem*. Department of Aeronautics and Astronautics of Stanford University, Stanford, California, 2003.
- [6] Buonanno M, Mavris D, *A new method for aircraft concept selection using multicriteria interactive genetic algorithms*. 43rd AIAA Aerospace Sciences Meeting and Exhibit , 10-13 January, Reno, Nevada, 2005, doi:10.2514/6.2005-1020.
- [7] Moreira EET, Schwening GS, Abdalla AM. An application of AHP, TOPSIS-Fuzzy and genetic algorithm in conceptual aircraft design. 4th CEAS Air and Space Conference, pp. 292-300, Linkoping, 2013.
- [8] Raymer D.P., *Aircraft design: a conceptual approach*, AIAA Education Series, 1989.
- [9] Chipperfield AJ, Fleming PJ, Polheim H, Fonseca CM. *Genetic Algorithm Toolbox – Matlab Tutoria*. Department of Automatic Control and System Engineering, 1996.
- [10] Golberg DE. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Longman Publishing Co., Inc. Boston, MA, USA ©, ISBN:0201157675, 1989.

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A.1 Appendix

Table A.1 Terminology

Variable	
W_{dg}	Design gross weight (lbs)
N_z	Ultimate load factor
S_w	Trapezoidal wing area (ft ²)
S_{csw}	Wing mounted control surface area (ft ²)
AR	Wing aspect ratio
$(t/c)_{wing}$	Wing root thickness/chord ratio
l	Wing tapering ratio
K_{door}	1.0 if no cargo door, 1.06 if one side cargo door, 1.12 if two side cargo doors, 1.12 if aft clamshell door, 1.25 if two side cargo doors and aft clamshell door
K_{LG}	1.12 if fuselage-mounted main landing gear, 1.0 otherwise
S_f	Fuselage wetted area (ft ²)
L_f	Fuselage structural length (ft)
D_f	Fuselage structural depth (ft)
B_h	Horizontal tail span (ft)
F_w	Fuselage width at hor. tail intersection (ft)
S_{ht}	Horizontal tail area (ft ²)
L_t	Tail length (ft)
K_y	Aircraft pitching radius of gyration (ft)
A_h	Hor. tail aspect ratio
S_e	Elevator area (ft ²)
H_t	Hor. tail height above fuselage (ft)
H_v	Vertical tail height above fuselage (ft)
S_{vt}	Vertical tail area (ft ²)
K_z	Aircraft yawing radius of gyration (ft)
A_v	Ver. tail aspect ratio
$(t/c)_{vt}$	Vertical tail root thickness chord ratio
W_{en}	Engine(s) weight (lbs)

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