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Preliminary Aircraft Design Optimization Using Genetic Algorithms

Imran Ali Chaudhry, Ali Ahmed

National University of Sciences & Technology, Sector H-12, Islamabad, Pakistan
imranchaudhry-cae@nust.edu.pk

Abstract: Aircraft design is a highly nonlinear problem and inherently multidisciplinary activity that involves thousands of design variables and different models and tools for various aspects of design. A spreadsheet based genetic algorithm (GA) approach is presented to optimize the preliminary design of an aircraft. A domain independent general purpose genetic algorithm is proposed to implement the optimization routine. Objective function used for the design evaluation is the Breguet. A total of sixteen design variables are considered in the optimization process. It has also been demonstrated that the proposed approach can be adapted to any objective function without changing the optimization routine. The model is applicable to commercial airliner as well as a multirole jet fighter. The proposed model has been validated against known configurations of various aircraft.
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Keywords: Genetic Algorithm (GA); Aircraft Design; Breguet Range equation; Spreadsheet

1. Introduction

Aircraft design is a tedious and prolonged exercise involving complex interdependence of a wide range of variables. The optimized values of these variables or their best possible combination only yield an effective, reliable and cost-effective aeroplane. The most efficient, reliable, fastest, lightest and cost effective aeroplane can be termed as an ideal aircraft, however, aircraft design is a compromise of different aspects because maximizing one capability would render another to an undesired degree. Therefore, a healthy compromise between all the desired qualities is the ultimate goal of a designer. The constraints dictate the values of the design variables so their ranges have to be kept in the realistic domain.

Aircraft design is considered to be a separate discipline of aeronautical engineering which is different from the other analytical disciplines such as propulsion, aerodynamics, controls, and structures. An aircraft designer should be well versed in these and many other specialties. Design is not only the actual layout, but also analytical processes that are used to determine what is to be designed and how the design should be modified to meet the requirements.

This paper attempts to use genetic algorithms (GA) to optimize preliminary aircraft design parameters to maximize the range of the aircraft. The proposed approach has been implemented in a spreadsheet environment using proprietary software as an add-in to the Microsoft Excel™ software.

2. Design Process

People involved in design never seem to agree where the design process begins. The designer thinks it starts with a new airplane concept. The sizing specialist knows that nothing can begin until an initial estimate of the weight is made. The customers, whether civilian or military, feel that the design begins with their requirements which are set by prior design trade studies. Thus, the concepts are developed to meet requirements. So is the case of other two parameters of design wheel. There are three major phases of aircraft design (Raymer, 2006) are: conceptual design followed by preliminary design then detailed design. The three major phases along with requirement of each phase are depicted in Figure 1.

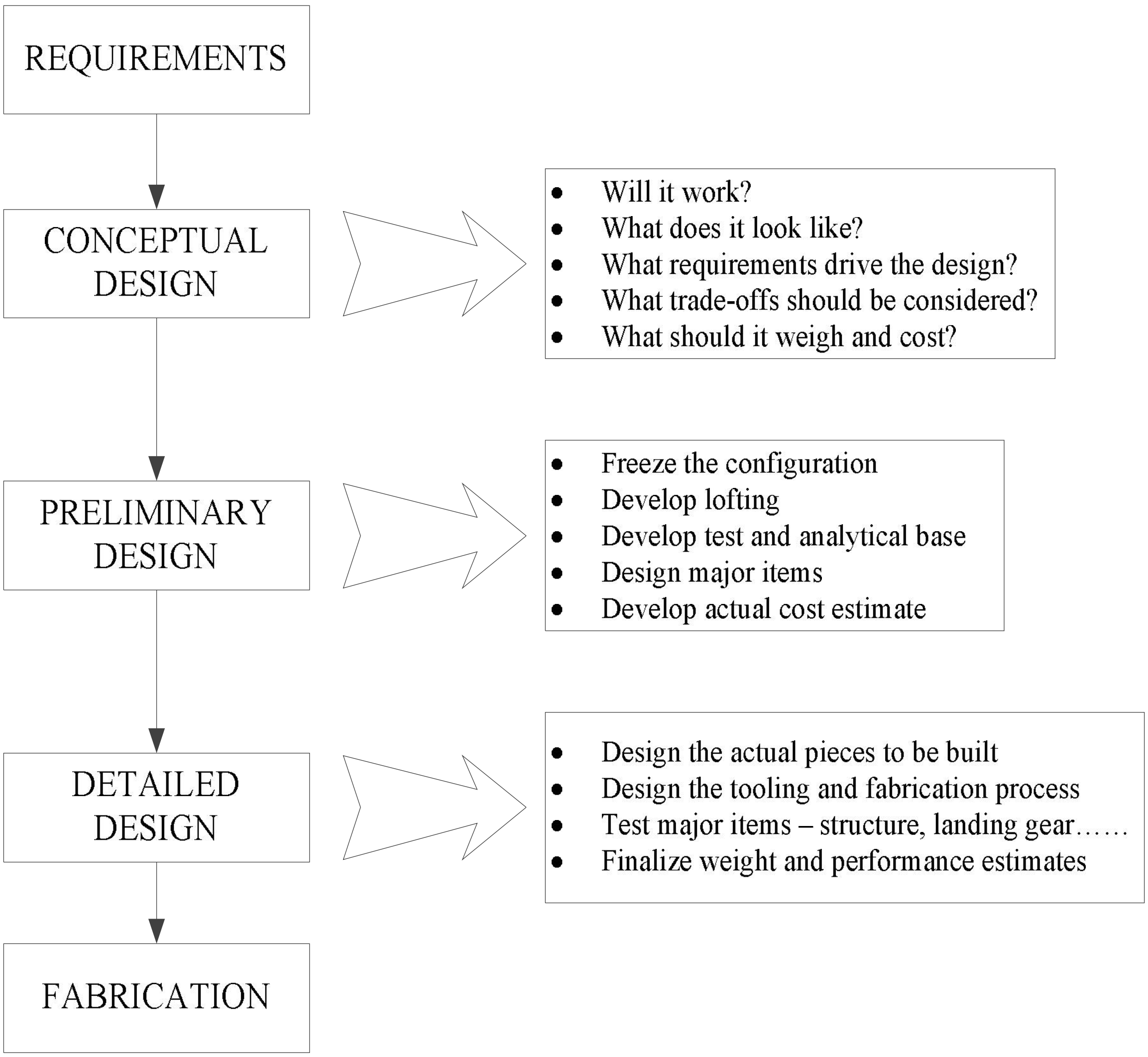

Figure 1. Aircraft design Phases

The conceptual design of the aircraft starts with the study of many feasible configurations in some detail, with the aim of achieving the mission requirements of the new aircraft; considering certain safety and operational criteria (Martinez & Hernandez, 1999 and Jayabalan et al., 2005). Conceptual design is subjected to an optimization process called the preliminary design. As a result one concept is finally chosen as the best compromise for all requirements and specifications. Preliminary design process, also called 'frozen configuration', goes through somewhat complete aerodynamic, flight mechanic and structural studies.

Fielding (1999) described that the most important stage of the aircraft design process is to define the correct set of requirements for future design; these requirements are called design specifications. These inputs require inputs from a variety of discipline and are dependent upon various design / airworthiness standards. The design process evolves through various information which include; airframe dimensions and shapes, performance parameters, static and dynamic loads, quality standards, certification criteria, and cost constraints, etc. (Gundlach, 2004). The various variable and constraints in the design process are interdependent thus for efficient design workflow the relations ship between various success of information must be known and the feedback loops are to be built into the design process (Sobester and Keane, 2006). Jayabalan et al. (2005) stated that aircraft design process includes finding an aerofoil shape by testing, do a sizing and performance optimization and integrating it together with the other parts of the aircraft, i.e. payloads, propulsion systems, controls etc.

3. Related Research

Bramlette and Bonehard (1991) discuss optimizing aircraft design when the task is posed as that of optimizing a list of parameters. They used real number representation for Genetic Algorithms and generated a large number of initial population members and worked only with the best ones.

Kroo et al. (1994) consider large-scale aeronautical systems and describe improved methods for multidisciplinary design and optimization of preliminary design. They evaluate a variety of implementation strategies with the development of efficient decomposition and optimization tools based on genetic algorithms.

Rasheed et al. (1997) devise a genetic algorithm for continuous design space search and define new genetic operators corresponding to the properties and structures of the engineering design domains. Finally the GA is applied to design of conceptual supersonic aircraft. Bos (1998) uses a procedure based on a hybrid genetic / gradient-guided optimization algorithm for the design of a second-generation supersonic transport aircraft. Obayashi (1998) examines the evolutionary algorithm for optimization of aircraft design and apply it to multidisciplinary design optimization (MDO) of aircraft planform shapes.

Daberkow and Marvis (1998) apply a feed-forward neural network to conceptual and preliminary aircraft design. They demonstrate that neural networks prove to be a more suitable alternative with improved performance. Parmee and Watson (1999) use a multi-objective optimisation approach that utilizes a genetic algorithm (GA) for the preliminary design of airframes. The use of parallel GA's produces a linear decrease in running time for the method bringing the whole process within an acceptable time frame, the results suggest that quicker less detailed runs can easily be achieved by using smaller population sizes.

Jun and Song (1999) also apply Genetic algorithm combined with fuzzy mathematics for the conceptual / preliminary aircraft design. Ng and Leng (2002) apply GAs to conceptual design of a micro-air vehicle. The chose six design parameters namely: angle of attack, main wing twist angle, winglet span, main wing chord length, main wing taper ratio and winglet taper ratio in their study. They compare the performance of using genetic algorithms with well-established non-linear optimization method based on sequential quadratic programming and demonstrate that as compared to other methods, GAs are efficient in escaping from escape from local minima and move towards the global optimum solution.

Ali and Behdinan (2002) apply GA for the conceptual design of an aircraft. Authors demonstrate that GAs can provide a reasonable aircraft design in a short amount of time compared with the traditional design techniques. Finally they compare the GA optimized aircraft shape and configuration with that of the existing aircraft. Results indicated that the GA is a powerful multi-disciplinary optimization and search tool, that is capable of managing and reforming numerous aircraft design parameters, to arrive at aircraft conceptual designs that are both efficient and cost effective.

Raymer (2002) applies multidisciplinary optimization methods for Aircraft Conceptual Design process. The author incorporates aircraft conceptual design analysis codes into various optimization methods including Orthogonal Steepest Descent (full-factorial stepping search), Monte Carlo, a mutation-based Evolutionary Algorithm, and three variants of the Genetic Algorithm. These methods are then compared for four aircraft concepts: a flying wing UAV, a commercial airliner, an advanced multirole export fighter and a general aviation twin of novel asymmetric configuration.

Roth and Crossley (2003) employ genetic algorithms in the aircraft design to determine which of the design variables should be changed and by what magnitude. They only consider design variables associated with the aircraft wing. Bandte and Malinchik (2004) employ an interactive evolutionary process for an aircraft design. The authors demonstrate that aircraft design solutions presented achieve better results than a previously published solution. Kroo (2004) also describes the use of evolutionary design methods in aeronautics. Ghorbany and Malek (2005) use genetic algorithms aircraft conceptual design for a short take-off and landing aircraft. They use minimization of life cycle cost as the objective function.

Vankan et al. (2006) present a response surface optimization approach for aircraft design that is implemented in MATLAB. Authors conclude that a key benefit of this approach is that large numbers of interesting design points can be found relatively quickly with less computationally expensive analyses, whilst maintaining a reasonable accuracy. Amadori et al. (2008) propose a framework for aircraft conceptual design which is a multidisciplinary optimization tool based on genetic algorithms for defining and refining aircraft designs, with respect to its aerodynamics, performance, weight, stability and control.

Marta (2008) describes application of genetic algorithms to preliminary aircraft design. The author studies the effects of varying different GA parameters on the algorithm efficiency. Alonso et al. (2009) describe set of procedures employing simulation and neural networks for aircraft design optimization. Zhiping and Yuxing (2010) study Parametric Optimization Design of Aircraft and propose an improved parallel multi-objective tabu search (PMOTS) algorithm. They also present a hybrid parallel multi-objective tabu search (HPMOTS) algorithm which combines the PMOTS algorithm with the non-dominated sorting-based multi-objective genetic algorithm (NSGA). The computational analyses indicate that HPMOTS is far more superior to PMOTS.

4. Problem Statement

The problem statement for preliminary aircraft design would be: determine the values of restricted design variables such that the range of the aircraft *R*, as given by Breguet range equation is maximized. The Breguet range equation is given by (Kroo, 2003):

$$R = \frac{V}{SFC}\frac{L}{D}\ln\left(\frac{W_i}{W_f}\right) \qquad (1)$$

where

V	=	Cruise velocity
L	=	Airplane lift
SFC	=	Specific fuel consumption at cruise speed and altitude
D	=	Airplane drag
W_i	=	Initial airplane weight
W_f	=	Final airplane weight

The objective is to maximize the range of the aircraft. The right-hand side terms in equation 1 can be estimated by combining several estimates described in Kroo (2003), using the design variables whose values are given in Table 1.

Two different aircraft types i.e., a commercial airliner and a multirole jet fighter, are considered in the paper. Hence, two different models, one for each type is built for optimization.

5. Genetic Algorithms

Genetic Algorithms (GAs) belong to a class of search methods that are especially suited for solving complex optimization problems. GAs were first introduced by Holland (1975). They transpose the notions of natural evolution to the world of computers, and imitate natural evolution. A GA functions by generating a large number of possible solutions to a given problem. Each solution is then evaluated against a “fitness value” to determine the parents. These solutions after crossover and mutation breed new solutions. Fitter solutions are more likely to reproduce as compared to less "fit". In successive iterations, best solutions (parents) are allowed to produce new solutions (children). The worst members of the population die off to make way for the fitter individuals. A detailed introduction to GA’s is given in Goldberg (1989). GAs have successfully been applied in the aircraft design (Rasheed et al. 1997, Bos 1998, Obayashi 1998, Parmee & Watson 1999, Jun & Song 1999, Ng & Leng 2002, Bandte & Malinchik 2004, Kroo 2004, Ghorbany Malek 2005, Marta 2008).

6. GA Implementation

In the present study GA is applied to the preliminary aircraft design in a spreadsheet environment. The model was made on the basis of the conceptual design by Raymer (2006). Two models were made essentially for a transport airliner and an airforce multi-role jet fighter. The models were developed separately according to the respective equations of both types. The model follows a methodological approach where a segment of the flight path or the mission profile is taken i.e. the cruise segment. For this segment the range was taken as the objective function to be the basic entity to be optimized. All the relationships were built to compute the equation for range, the Breguet Equation.

For genetic algorithm implementation, we employ a commercially available GA namely Evolver™ (1998), that functions as an add-in to the spreadsheet environment i.e., Microsoft Excel™. The aircraft design optimization model is developed using spreadsheet’s built in functions. Figure 2 shows the spreadsheet-GA integration.

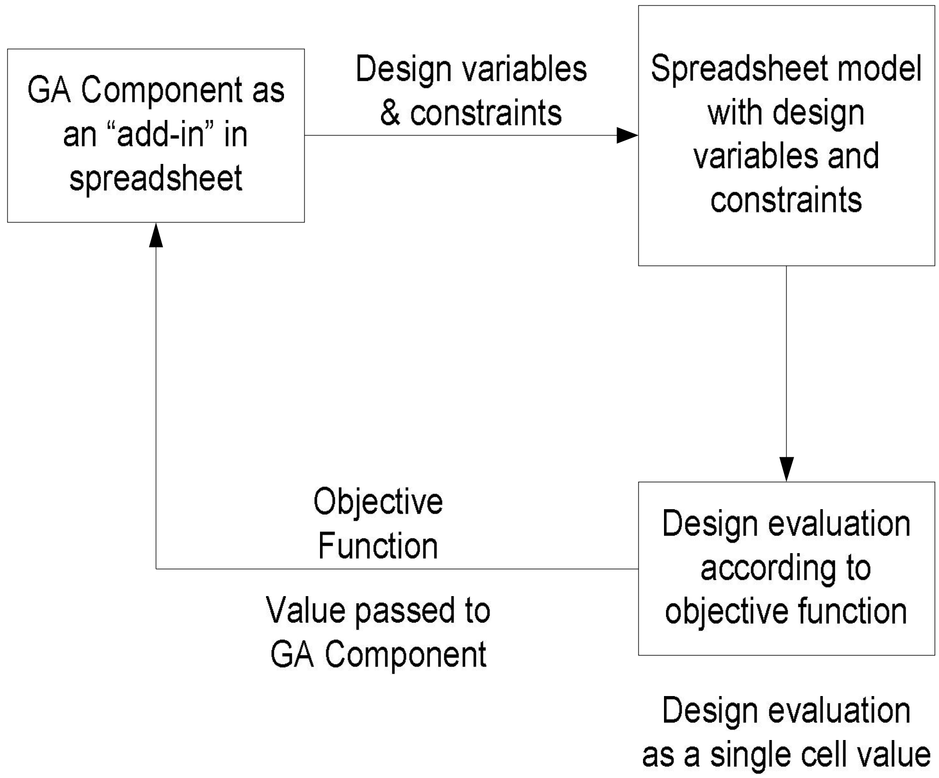

Figure 2 Spreadsheet-GA Integration

The fitness/objective function value is passed on to the GA component as a single cell value for the evaluation of the design.

Two models were made essentially for a transport airliner and a multirole jet fighter. The models were developed separately according to the respective equations of both types. The model follows a methodological approach where a segment of the flight path or the mission profile is taken i.e. the cruise segment. For this segment as stated earlier, the range was taken as the objective function to be the basic entity to be optimized. All the relationships were built to compute the equation for range, the Breguet Equation.

Keeping in view the historical trends, a total of 16 and 14 design variables are used to develop the models for commercial airliner and a multirole jet fighter respectively. The design variables for the commercial airliner and multirole jet fighter along with the range of each are given in Table 1 and 2 respectively.

Table 1. Design Variables for Commercial Airliner

S No	Variable Name	Admissible Values Min	Admissible Values Max
1	Takeoff Weight	150000 lb	180000 lb
2	Wing Span	80 ft	125 ft
3	HT Span	30 ft	70 ft
4	VT Span	20 ft	50 ft
5	Mach No	0.5	0.8
6	Seating Capacity	150	195
7	Aspect Ratio	7	10
8	SFC	0.0002/hr	0.00027/hr
9	Altitude	25000 ft	37000 ft
10	Fuselage Length	110 ft	150 ft
11	Fuselage Dia	12 ft	18 ft
12	Wing Sweep	25º	30º
13	Angle of Attack	3°	5°
14	Ultimate Load Factor	2	4
15	T/C Wing	0.14	0.2
16	Taper Ratio Wing	0.4	0.5

Table 2. Variables for Multirole Jet Fighter

S No	Variable Name	Admissible Values Min	Admissible Values Max
1	Takeoff Weight	25000 lb	33000 lb
2	Wing Span	25 ft	35 ft
3	VT Span	6 ft	9 ft
4	Mach No	0.5	0.8
5	Aspect Ratio	1.6	2.2
6	SFC	0.00023/hr	0.00027/hr
7	Altitude	25000 ft	37000 ft
8	Fuselage Length	40 ft	60 ft
9	Fuselage Dia	4 ft	10ft
10	Angle of Attack	3°	5°
11	Ultimate Load Factor	6	9
12	T/C Wing	0.04	0.06
13	T/C VT	0.05	0.06
14	Max Mach	1.8	2.2

6.1 Chromosome Representation

Direct representation is used for the representation of the chromosome where each gene represents a particular design variable. Thus for a commercial airliner the chromosome length would be of sixteen genes, which is actually equal to the number of design variables. Similarly, for multi-role jet fighter the chromosome length would be of fourteen genes. Thus for each of the gene a number is generated between the defined range to find the best possible combination of values that gives the maximum value for the objective function given in equation 1.

6.2. Reproduction / Selection

In this research steady state reproduction as reported in GENITOR GA (1988) is used, thus in each iteration only one worst performing organism is replaced instead of replacing the whole generation. In case of a steady state reproduction, all the genes are not lost, as is the case in generational replacement where after replacement, many of the best individuals may not produce at all and their genes may be lost. Steady-state reproduction is a better model of what happens in longer lived species in nature. This allows parents to nurture and teach their offspring, but also gives rise to competition between them. The value of the objective function for a particular chromosome is a measure of its fitness.

6.3. Crossover Operator

Uniform crossover is performed by the GA routine. This means that instead of chopping the list of variables in a given scenario at some point and dealing with each of the two blocks (called "single-point" or "double-point" crossover), two groups are formed by randomly selecting items to be in one group or another. Traditional *x*-point crossovers may bias the search with the irrelevant position of the variables, whereas the uniform crossover method is considered better at preserving schema, and can generate any schema from the two parents. In uniform crossover, instead of chopping the list of variables in a given scenario at some point and dealing with each of the two blocks, two groups are formed by randomly selecting items to be in one group or another. Figure 3 shows uniform crossover.

P1	1	1	0	0	1	0	1	0
P2	0	0	1	0	0	1	1	1
Mask	1	0	0	1	0	1	1	0
Child	1	0	1	0	0	0	1	1

Figure 3. Uniform crossover

In uniform crossover operator, mixing ratio or crossover rate decides which parent will contribute each of the gene values in the offspring chromosome. This allows the parent chromosomes to be mixed at the gene level rather than the segment level.

Consider the two parents in Fig. 3 which have been selected for crossover. Parent *P1* has been colored green while parent *P2* yellow. A random mask is generated corresponding to the crossover rate. If the crossover rate is 0.5, approximately half of the genes in the offspring will come from *P1* and the other half will come from *P2*. Below the second parent is the random mask generated corresponding to the crossover rate. The child is produced by taking bit from *P1* if the corresponding mask bit is 1 or the bit from *P2* if the corresponding bit is 0. The color of the child chromosome represents the mixing of genes if the crossover rate is 0.5.

6.4. Mutation operator

The purpose of the mutation is to ensure that diversity is maintained in the population. It gives random movement about the search space, thus preventing the GA becoming trapped in "blind corners" or "local optima" during the search. The GA in this research performs mutation by looking at each variable individually. A random number between 0 and 1 is generated for each of the variables in the organism, and if a variable gets a number that is less than or equal to the mutation rate (for example, 0.06), then that variable is mutated. The amount and nature of the mutation is automatically determined by a proprietary algorithm. Mutating a variable involves replacing it with a randomly generated value (within its valid min-max range).

7. Computational Results

The simulations have been run on a Dual Core 2.1 GHz computer having 1 GB RAM. For each of the run, the following parameters have been used: population size = 65, crossover rate = 0.65, mutation rate = 0.01, and stopping criteria = 80,000 trials, which corresponds to approximately 1 min on a Dual Core 2.1 GHz computer having 1 GB RAM.

The initial model was run with restricted variables. In the initial model, only eight variables namely: take-off Weight (W_o), wing Span (b), horizontal tail span (bht), vertical tail span (bvt), Mach no (M), altitude (h), aspect ratio (AR) and seating capacity (n) were considered for optimization. The model was verified against known configurations of various existing commercial airliners. As stated earlier range has been used as an objective function. Table 3 gives the value of range and %age error for existing commercial airliners vis-à-vis the range calculated from the proposed model.

The actual range value and that calculated from the proposed model are quite close. The accuracy would increase as the number of design variables is increased as some of the values in the model have been assumed to be constants for a particular type of an aircraft.

In the second phase the model was revised to include additional variables, thus increasing the number of variable to 16. The additional variables were: fuselage length, fuselage diameter, specific fuel consumption, wing sweep, angle of attack (AOA), ultimate load factor, wing thickness to chord ratio and wing taper ratio. Table 4 gives the range and %age error for the same aircraft as mentioned in Table 3.

It is evident from Table 3 and 4 that except for Boeing 747-100, increasing the number of variables increases the accuracy of the model.

After validation of the model, the simulations were run to find the optimized values of design variables. The optimized values found after one run for the variables are given in Table 5. The corresponding value of range of the aircraft was 2876 nm.

Table 6 shows the average results after 30 runs. The average value of range after 30 runs was 2878 nm. Similar exercise was carried out for a multirole jet fighter. Optimized values for the variables after one and 30 runs are given in Table 7 and 8 respectively.

The range calculated for a fighter aircraft after one run was 817 nm, while the average range after 30 runs was 821.7 nm.

Table 3. Results of verification – Initial model

S. No	Aircraft	Actual Range (Nm)	Model Calculated Range (Nm)	%age Error
1	Airbus A318-100	3250	3059	6%
2	Boeing 747-100	5300	5170	4%
3	DC 8-32	4116	3630	12%
4	DC 8-63 CF	1913	1695	11%
5	Boeing 737-700	1585	1681	8%
6	Airbus A320-200	3000	2878	4%

Table 4. Results of verification – Final model

S. No	Aircraft	Actual Range (Nm)	Model Calculated Range (Nm)	%age Error
1	Airbus A318-100	3250	3059	6%
2	Boeing 747-100	5300	5170	4%
3	DC 8-32	4116	3630	12%
4	DC 8-63 CF	1913	1695	11%
5	Boeing 737-700	1585	1681	8%
6	Airbus A320-200	3000	2878	4%

Table 5. Values of variables for a commercial airliner found after first run

S. No	Optimized Variable	Value Obtained	S. No	Optimized Variable	Value Obtained
1	Take-off Weight	164,179 lb	9	Fuselage Length	118 ft
2	Wing Span	122 ft	10	Fuselage Diameter	15 ft
3	Ht Span	53 ft	11	Wing Sweep	25°
4	Vt Span	20 ft	12	SFC	0.00024 /hr
5	Mach	0.79	13	Ultimate Load	3.5
6	Altitude	36830 ft	14	AoA	4°
7	Aspect Ratio	10	15	Wing T/C	0.14
8	Seats	195	16	Taper Ratio	0.45

Table 6. Values of variables for a commercial airliner found after 30 runs

S. No	Optimized Variable	Value Obtained	S. No	Optimized Variable	Value Obtained
1	Take-off Weight	164,109 lb	9	Fuselage Length	120 ft
2	Wing Span	124 ft	10	Fuselage Diameter	15 ft
3	Ht Span	51 ft	11	Wing Sweep	25°
4	Vt Span	20 ft	12	SFC	0.00023/hr
5	Mach	0.79	13	Ultimate Load	3.5
6	Altitude	36840 ft	14	AoA	4°
7	Aspect Ratio	10	15	Wing T/C	0.14
8	Seats	195	16	Taper Ratio	0.45

Table 7. Values of variables for a multirole jet fighter found after first run

S. No	Optimized Variable	Value Obtained	S. No	Optimized Variable	Value Obtained
1	Take-off Weight	29,046 lb	8	Fuselage Length	49 ft
2	Wing Span	27.3 ft	9	Fuselage Diameter	7 ft
3	Max Mach	2.2	10	Wing T/C	0.05
4	VT Span	6.2 ft	11	SFC	0.00024 /hr
5	Mach	0.80	12	Ultimate Load	7
6	Altitude	36870 ft	13	AoA	3°
7	Aspect Ratio	1.9	14	VT T/C	0.04

Table 8. Values of variables for a multirole jet fighter found after 30 runs

S. No	Optimized Variable	Value Obtained	S. No	Optimized Variable	Value Obtained
1	Take-off Weight	29,024 lb	8	Fuselage Length	50 ft
2	Wing Span	27.1 ft	9	Fuselage Diameter	7 ft
3	Max Mach	2.2	10	Wing T/C	0.05
4	VT Span	6.1 ft	11	SFC	0.00025 /hr
5	Mach	0.80	12	Ultimate Load	7
6	Altitude	36930 ft	13	AoA	3°
7	Aspect Ratio	1.8	14	VT T/C	0.04

8. Comparison of Results

The optimized values found by the model were compared with different available configurations. The closest configuration of a functional aircrafts to the values obtained by the proposed was Airbus A320-200 for the commercial airliner and Mirage 2000 for the multirole jet fighter. Table 9 and Table 10 give the comparison of different variables with Airbus A320-200 and Mirage 2000 respectively.

Table 9. Comparison with Airbus A320-200

S No	Variable Name	Calculated Values	Airbus A320-200
1	Take-off Weight	164109 lb	170000 lb
2	Wing Span	124.7 ft	111 ft
3	HT Span	50.2 ft	57 ft
4	VT Span	20.03 ft	22 ft
5	Mach No	0.79	0.8
6	Seating Capacity	195	180
7	Aspect Ratio	10	9.8
8	SFC	0.00023 /hr	0.00024 /hr
9	Altitude	36840 ft	37000 ft
10	Fuselage Length	120 ft	123 ft
11	Fuselage Diameter	15 ft	13 ft
12	Wing Sweep	25º	25º
	Range	**2878 nm**	**3000 nm**

Table 10. Comparison for Mirage 2000

S No	Variable Name	Calculated Values	Mirage 2000
1	Take-off Weight	29024 lb	30420 lb
2	Wing Span	27.13 ft	29 ft
3	VT Span	6.1 ft	7 ft
4	Mach No	0.79	0.8
5	Aspect Ratio	1.8	1.9
6	SFC	0.00025/hr	0.00025/hr
7	Fuselage Length	50 ft	47 ft
8	Fuselage Diameter	7 ft	7.6 ft
9	Max Mach	2.2	2.2
	Range	**821.7 Nm**	**837 Nm**

9. Conclusions

This paper has attempted to use GAs for optimizing the aircraft range for preliminary aircraft design for a commercial airliner and a multirole jet fighter. In preliminary aircraft design problem we define only the major aircraft characteristics. After this we move to the detailed aircraft design.

Results in the current research indicate that by increasing the number of variables, we can increase the accuracy of the model. The approach has demonstrated that it is very easy to customize the solution for any objective function without disturbing the logic of the GA routine, thus making it a general purpose solution approach.

Even with small number of design variables, the results produced in this research were very close to the already available configurations of aircraft. The spreadsheet-GA implementation has been found to be easy to implement and customizable to any condition without changing the GA routine, which makes it a domain-independent approach. Furthermore, spreadsheet environment also enables carrying out of what-if analysis. The approach is not a customization of the GA logic rather it only modifies the model in spreadsheet without changing the actual GA routine.

Corresponding Author:
Dr. Imran Ali Chaudhry
National University of Sciences & Technology
Sector H-12
Islamabad, Pakistan
E-mail: imranchaudhry-cae@nust.edu.pk

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