Conceptual Aircraft Design – A Genetic Search and Optimization Approach

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ABSTRACT

With recent advancements of computers and the advent of a search and optimization tool such as the genetic algorithm (GA), the ability to manipulate numerous aircraft design parameters in reasonable amount of time becomes feasible. It is from this standpoint that when one examines the aircraft design process, that is, the lengthy time and effort spent creating and integrating aerodynamics codes, sizing routines and performance modules, that the GA becomes beneficial. Consequently, a GA was created and employed as a tool to explore possible aircraft geometries that are more efficient and less costly than an existing design. The adaptive penalty method is employed in the GA to handle all constraints imposed on the design. In addition, the effects of the adjustments for varying degree of selection and crossover intensities and types on the aircraft evolutionary process are studied. A design study is also conducted to 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.

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NOMENCLATURE

W_0 = gross weight (lbs.)
C_r = wing root chord (ft)
C_t = wing tip chord (ft)
b = wing span (ft)
S = gross wing area (ft^2)
S_{ht} = horizontal tail area (ft^2)
l_{fus} = length of the fuselage (ft)
S_t = gross tail area (ft^2)
V_h = horizontal tail volume coefficient
V_v = vertical tail volume coefficient
F = stick force (lb.)
$C_{m\alpha}$ = change of pitching moment coefficient with angle of attack
C_{mo} = coefficient of moment at zero angle of attack

INTRODUCTION

A word that often comes to mind in aircraft design is compromise. In fact, it can be argued that the entire aircraft design process entails finding the correct balance or compromise between numerous design variables and design constraints. Moreover, the traditional design techniques usually require the expertise of designers and engineers to arrive at an efficient design. The pitfall of such an approach is that it relies entirely on designer's and engineer's knowledge and creativity. Hence the problem of human error cannot be ruled out. Unfortunately, each design discipline is limited to a subset of configuration parameters, goals, and constraints due to the highly interdisciplinary process, which involves a high number of variable couplings [8]. Hence, due to the processes entailed in the traditional design approach, the designer may not fully grasp how the design objectives from a particular design discipline conflicts with another.

Finally, the traditional design approach entails lengthy meeting time and large sums of money to create and integrate the various disciplines of aircraft design.

On the other hand, the GA was developed to eliminate or at best minimize the problems, time and cost encountered in the traditional design approach.

It can be argued that the genetic algorithm is one of the most robust evolutionary algorithms in use today. Furthermore, GAs has found extensive application in the field of research and development, especially in areas where optimization is the key objective. This paper brings a focus on the application aspect of GAs in aircraft conceptual design.

For small spaces, classical exhaustive methods usually suffice; however, for larger spaces special artificial intelligence techniques must be employed. Genetic algorithms are among such techniques; they are stochastic algorithms

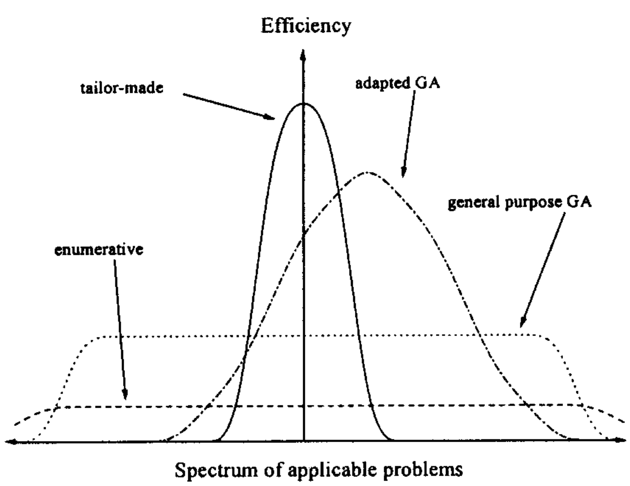


Figure 1: Comparison of the robustness of genetic algorithm- based and more traditional methods (adapted from Ref. 3)

whose search methods model some natural phenomena: genetic inheritance and Darwinian strife for survival [1]. The range of application and robustness of the GA compared to other methods is presented in figure 1. As figure 1 indicates, even though highly problem specific questions can outperform the GA, their range of application is very small. On the other hand, GA's are quite robust, and through random operators can be made efficient.

Despite its efficiency some have argued that there are some pitfalls and challenges in assuming that the GA is a true optimization tool. Moreover, since no gradient is used in the GA search approach there is no proof of convergence. Hence the GA lacks a reliable means of asserting optimality. Genetic algorithms usually get close to an optimum point but can occupy long computing time to locate it exactly. Consequently, researchers taking realizing this problem have created hybrid GAs that employs the traditional gradient optimization approach at the end of the GA search to quickly find the optimum. Nonetheless, often it is more effective to run the GA for several cases to near optimality rather than run a single case to exact optimality [5]. Even though the GA may be less effective as a true optimization method it can be quite efficient as a technique to narrow the vast design space to the most interesting areas, which is a major goal of conceptual design [6].

PREVIOUS WORK

Numerous attempts have been made to explore the capabilities of the GA to find plausible and better combinations of design variables in aircraft conceptual design. Crispin [7] was among those that first employed GA in aircraft design process and found it a usable tool in obtaining reasonable and feasible aircraft designs. Later the work of Crossley and et. al. [8], studied and documented the effects of incorporating a more through conceptual design process and thereby was able to show the effectiveness of the GA in obtaining feasible aircraft and helicopter designs. In these work the author stressed the importance and effectiveness of the GA in saving time and money in the initial design process. In addition Perez and et. al. [2,18] conducted some research employing GA in aircraft conceptual design. This work brought a focus of GAs as an optimization tool and presented a comparison between the GAs design and the existing design. From the results obtained it was showed that the GA generated designs led to a total weight saving of 5%. These works are among few that have been conducted in the aerospace industry. Others research investigating and applying the GA to transonic design of airfoils, wing design for minimum drag, geometry optimization of aircraft, stability and control in aircraft conceptual design etc. ca n also be found in the literature.

FUNCTIONALITY of GA as an OPTIMISATION TOOL

Genetic algorithms are a class of general-purpose (domain independent) search methods, which strike a remarkable balance between exploration and exploitation of the search space [1]. The GA has proven to outperform the more traditional gradient methods of optimization. These methods are limited in application since they require finding the derivative, they are constrained to small domains whose first derivative must be continuous and they can handle only a small number of variables. As figure 1 suggest, given enough information about the search space it will always be possible to construct a search method that will outperform the GA. However, obtaining such information is for many problems almost as difficult as solving the problem itself [3]. Thus, the robustness of GAs makes them an ideal candidate for an optimization tool.

The Basic GA

Genetic algorithm is designed to mimic evolutionary process of nature. The idea is that, given a certain problem representation, the GA is able through repeated use of genetic operators, that is, selection, crossover and mutation, to combine those parts of a solution that are necessary to form a globally optimal solution [5]. A GA searches and optimizes by means of multiple searching points or solution candidates (POPULATION BASED SEARCH). Each individual in the population is represented by a string (chromosome), which carries the variables of design (genes). In genetic algorithms each individuals represents a certain solution to a given problem. The quality of this solution is expressed by a so-called fitness value. An individual with a higher fitness has a higher chance of surviving and reproducing.

Consequently, a MATLAB [20] coded binary genetic algorithm was created to explore its capabilities as an aircraft conceptual design tool.

PENALIZING STRATEGIES

The central problem in applying a GA to the aircraft design is how to handle the constraints. It is very common for the constraint-handling scheme to influence performance [5]. As a result, the common and efficient penalty strategy will be employed in this study. Before the fitness of the individual can be evaluated the population of strings must first be decoded into real numbers since the objective function can only read such values. The fitness function is the product of the objective function times the penalty value. The main role of the penalty strategy in the GA is that it unconstraint our problem by multiplying a certain penalty value (indicative of the degree of constraint violation) to the objective function for any violation of the constraints. This multiplication will have the effect of adding ‘weight’ to our fitness value thereby decreasing its goodness if we are minimizing. Hence 'weight' plays the role of penalties if a potential solution does not satisfy them [9]. One major advantage of the penalty strategy compared to other methods is that it does not disregard the infeasible solutions; instead it uses these solutions in such a way to aid the search to better solution. In addition, other advantage that this method has over the traditional approaches is that it is non-parameterized and most importantly it is problem independent [9, 10].

For minimization:
Fitness = objective value * penalty value

$$\text{Fitness} = f(x)*p(x) \tag{1}$$

Where f(x) is the objective value and p(x) is the penalty value.

p(x)=1 if feasible
p(x)>1 otherwise

The penalty value is computed using the method outlined below:

$$p(x) = 1 + \frac{1}{m}\sum_{i=1}^{m}\left(\frac{\Delta bi(x)}{(\Delta bi)_{\max}}\right)^{\alpha} \tag{2}$$

where: $\Delta b_i(x) = \max(0, g_i(x))$

$$(\Delta bi)_{\max} = \max(\varepsilon, \Delta b_i(x) | x \in p(x))$$

where:
g_i = the degree of violation of the constraints and is dynamically scaled according to the best solution found in the population set; ε = small positive value that is used to avoid division by zero when calculating p(x); m= number of constraints. $\Delta bi(x)$ = degree of violation of the constraint i for the chromosome x; $(\Delta bi)_{\max}$ = maximum violation in constraint i among the current population; α = value used to adjust the severity of the penalty function. Traditionally, α varies between 1 and 3.

REPRODUCTION STRAGEGIES

The GA under study employs two different reproduction schemes i.e. roulette selection and tournament selection, which assigns probabilities of selection depending on fitness values and the inverse scheme to scale fitness and maintain a differential between fitness values. The type of selection scheme influences the convergence quality of GA's, since the selection scheme is the part of the GA making the decisions. The goal of any selection model is to favor the proliferation of good individuals in the population [11, 22]. The effects of these schemes on the aircraft evolutionary process will be studied.

Inverse Scheme

Since GA's by nature optimizes via maximization, the problem of changing the GA process to a minimization arises. For minimization the fitter individual has the lower fitness or cost. Thus, in the selection process one must be able to transform the large number to a small number. To achieve this the inverse scheme will be employ. The basic concept of the inverse scheme comes form a simple logical deduction of – the result of inverting a large number is a small number [6]. The fitness values are scaled as follows:

$$F_i' = \frac{F_{\max} - (F_{\min}/a)}{F_i - (F_{\min}/a)} \tag{3}$$

where F_i' is the scaled fitness values; $F_{\max}$ and $F_{\min}$ are the maximum and minimum fitness values respectively; a is a value slightly greater than one and F_i is the fitness values.

Roulette Selection

Roulette Selection or fitness proportional selection assigns reproduction opportunities to an individual based on their relative fitness. Thus it is a stochastic process of selection, which will choose individuals on the basis of performance with respect to other individuals in the population. Individuals are selected and placed into a mating pool based on the relative fitness.

Tournament Selection

Apart from the population size and control parameters (i.e. probability of crossover and probability of mutation), the selection type – as will be evident- strongly influences the quality of convergence. There are many selection schemes that have been created all of which attempts to make the selection process more random, and to a larger extent, do what nature does. Tournament selection is quite random and closely mimics mating competition in nature. From the population, a fixed number of competitors (tournament size) are randomly selected. The individual with the highest fitness wins the tournament and is then placed in a mating pool. As the tournament size gets larger the selection intensity increases [21].

CROSSOVER STRATGIES

Without crossover, the average fitness of the population would climb until the fitness is equal to the fitness of the fittest member. Crossover provides a way whereby information from differing solutions can be melded together to allow for exploration of different parts of the search space. The impact of one-point, two-point and uniform crossover schemes will be studied to assess the effects of these schemes on the GA evolutionary process.

Uniform Crossover

Uniform crossover generalizes single and multi-point crossover schemes to make every locus a potential cross point. It is a more aggressive crossover operator that increases the chances that building blocks mix correctly, but also more building blocks are disrupted [21]. A crossover mask, the same length as the individual structure is created at random and the parity of the bits in the mask indicates which parent will supply the offspring with which bits [6]. Uniform crossover, like multi-point crossover, has been claimed to reduce the bias associated with the length of the binary representation used and the particular coding for a given parameter set [4,11].

MUTATION

Mutation serves the crucial role of forcing the population out of a static condition by introducing new genetic information to it. In some ways mutation provides for exploration of the search surface, because it strays away from the convergence path into new territory. Mutation becomes essential in later stages of the run when the population is converged and some the string highly resembles each other. Mutation is achieved by the random alteration of a bit; this simply means changing a 1 to a 0 and visa versa whenever the random number generated is less that the probability of mutation. In the program a dynamic probability of mutation is used to enhance mutation rates at the end of the population.

PROBLEM STATEMENT

This paper brings a focus on the application of the GA to the conceptual design of an aircraft with constraints in sizing, performance, and stability and control. In addition, a study will be conducted to analyze the evolution of the aircraft as the GA search progresses. The design variables chosen for optimization are given in table 1. The range of these variables is determined from historical and statistical data. The length of the bit string is determined from the range of these variables and the degree of accuracy required. The twenty one design variables along with the design process and constraints is utilized by the GA to find the correct balance or combinations of variables that will lead to better designs. Weight will be employed as the main parameter of study in the aircraft fitness function to optimize. A reduction of weight and the computing time required to arrive at efficient conceptual aircraft designs are the main goals of this research.

Table 1: Critical Design Variables

Design Variable	Variable Type	Variable Description	Variable Domain	String Length (# of bits)
W/S	(c)	Wing loading (lb/ft^2)	70-140	8
T/W	(c)	Thrust Weight Ratio	0.3-0.5	5
$C_{l\,max}$	(c)	Maximum Airfoil Lift	1-1.5	3
AR_w	(c)	Wing Aspect Ratio	6-12	7
λ_w	(c)	Wing Taper Angle	0.1-0.9	6
Λ_w	(c)	Wing sweep angle (deg)	0-50	9
t/c	(c)	Wing thickness	0.1-0.15	3
AR_{ht}	(c)	Horizontal tail Aspect Ratio	3-5	5
λ_{ht}	(c)	Horizontal tail Taper Ratio	0.2-0.6	4
Λ_{ht}	(c)	Horizontal tail Sweep angle (deg)	5-45	7
T_{Type}	(d)	Tail Type T Tail–0 Conventional-1	0-1	2
AR_{vt}	(c)	Vertical tail Aspect Ratio	0.7-1.2	1
λ_{vt}	(c)	Vertical tail Taper angle	0.3-0.9	5
Λ_{vt}	(c)	Vertical tail Sweep angle (deg)	35-55	4
N_{eng}	(i)	Number of Engines	2-4	7
Material	(i)	Material Type 0-conventional 1-Composite	0-1	1
$Nseats$	(d)	Seating arrangement (1-11)	2-11	4
l_t	(c)	Horizontal tail arm (ft)	40-100	8
S_t	(c)	Horizontal tail area (ft^2)	200-700	10
$C_{h_{\delta e}}$	(c)	Hinge moment due to Elevator deflection	-0.1 - -1	4
l_v	(c)	Vertical tail arm (ft)	40-100	8

Note: c-continuous, i-integer, d-discrete

DESIGN OBJECTIVES

The objective of this paper is to find the right combination of design variables that will provide the initial design layout to speed up the aircraft conceptual design process. This objective must be achieved with minimal constraint violation and combination of variables that leads to a practical and feasible conceptual aircraft designs.

The main optimization goal is to minimize the aircraft weight. The aircraft weight is directly related to the total cost of the aircraft. Furthermore it can be argued that an aerospace structure is a structure whose usefulness diminishes significantly with increasing weight [12].

FITNESS EVALUATION

The fitness function is geared towards weight minimization with adaptative penalty strategy employed to handle the constraints. In effect a multidisciplinary design optimization approach is taken whereby geometry, sizing, aerodynamics, performance and stability and control are analyzed and integrated.

Briefly the sizing routine is based on the 'rubber engine sizing methodology'. The aerodynamic characteristics are calculated using detail component buildup method adapted from reference 12. Performance characteristics for the aircraft brings a focus on satisfying federal aviation requirements during takeoff, climb, descent and landing as adapted from reference 12-17. Stability and control analysis is conducted assuming a minimum value for the static margin. This design discipline strongly correlates the aircraft geometry and layout. In all of the above aircraft design disciplines a total of fifteen design constraints are implemented.

The total weight of the aircraft can be subdivided in three main areas i.e. fuel weight, payload and empty weight of the aircraft.

The fuel weight is determined from the mission objectives and the intended use of the aircraft. Fuel fractions are then estimated using the mission profile and fuel consumption based on performance analysis. The weight of the payload is constant and is directly related to the number of passengers, crew and cargo. The empty weight is estimated using the component buildup method, with estimation techniques adapted from reference 12,13 and 14.

DESIGN CONSTRAINTS

The adaptive penalty method is used to handle all constraints imposed on the conceptual aircraft design process. This method multiplies the objective fitness value by a value greater than 1 if there is any constraints violation or 1 otherwise. A few constraints that are implemented in the aircraft design process are that related to the takeoff distance, the coefficient of moment with respect to the angle of attack and the stick force required by the pilot to trim the aircraft. So for example, the constraints that are necessary and sufficient in enduring that the aircraft is statically stable in pitch are as follows:

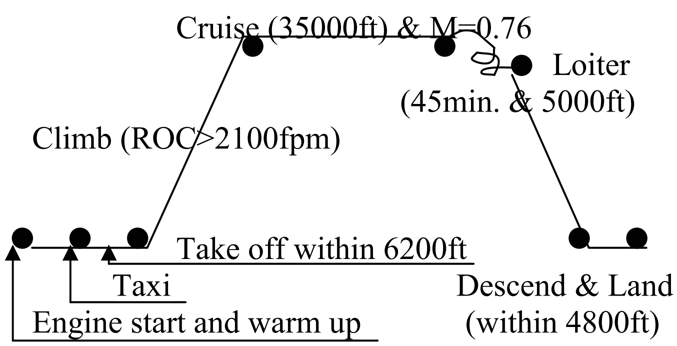
$$C_{mo} > 0$$

$$C_{m\alpha} = \frac{dC_m}{d\alpha} < 0$$

If for instance C_{mo} is greater than 0 and $C_{m\alpha}$ is less than 0 there is no constraint violation and the penalty term becomes 1, i.e. there is no constraint violation. On the other hand, if $C_{m\alpha}$ is less than zero but C_{mo} is less that zero then there is some constraint violation the penalty term is greater than 1, and in engineering terms means the aircraft cannot be trimmed. This implies that the aircraft is not flyable even though it is statically stable. If however the $C_{m\alpha}$ is greater than zero and C_{mo} is less than zero the aircraft is flyable, but it is statically unstable. In this case there is some degree of violation of the constraints and hence the penalty term is also greater than 1.

MISSION PROFILE

The mission profile is based on the type of aircraft used for study and comparisons, in this case the Boeing 717. The Boeing 717 is a medium size transport aircraft [19] and a typical mission profile is illustrated in figure2 below. For this study the number of passengers and crew is fixed and 110 and 6 respectively. In addition the average weight of crew and passenger is implemented into the program.



Payload 26950lbs. & $n_{ult.} = 3.5$ g's

Figure 2: Transport aircraft mission profile

RESULTS

The convergence history of the GA subjected to various selection and crossover strategies is shown in figure 3 while table 2 illustrates the design parameters obtained at each run.

Note it takes longer with weaker strategies such as one point crossover to locate reasonable design variables in the search space. Moreover, after 120 generation most of the runs has meet steady state and further changes in the design were not occurring. However, this is no indication that an optimal design has been reached, but it does prove that the GA is converging.

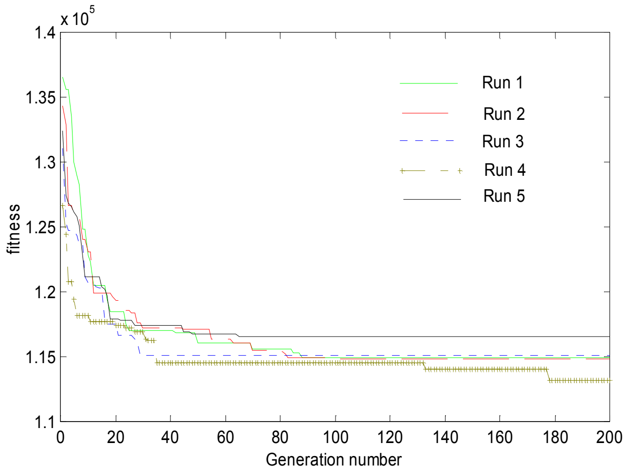


Figure 3: Convergence history for genetic algorithm conceptual aircraft designs for run 1 to 5

The results indicated in table 2 are based on a fixed probability of crossover and dynamically changing probability of mutation at every generation. A fixed population size of 80 is implemented with 200 generations used as the stopping criteria. There are a number of tradeoffs between population size and the number of generation needed to converge. What is really needed is a balance between population size, so that the GA is able to explore and, the number of generations, so that the GA is given enough time to converge to the most interesting areas of the search space. A small population size causes the GA to quickly converge on a local minimum because it insufficiently samples the parameter space.

On the other hand, a large population size takes too long to find and assemble the building blocks to the optimum solution [5]. Moreover, elitism strategy is employed to prevent the loss of a potentially good design by ensuring that its presence is maintained in the population at every generation until an even better design is located.

Table 2: GA Optimization results and Comparison

	Run 1	Run 2	Run 3	Run 4	Run 5
Crossover Type	1 point	2 point	Uniform	Uniform	2 point
Selection Type	Tourn.	Tourn.	Tourn.	Roul.	Roul.
Design	Variables				
W/S	105.41	95.26	99.37	97.17	96.08
T/W	0.31	0.3	0.3	0.3	0.3
$C_{l\ max}$	1.5	1.5	1.5	1.5	1.5
AR_w	6.15	6	6.05	6.05	6.0
λ_w	0.3	0.33	0.33	0.3	0.32
Λ_w	30.53	24.66	23.09	24.56	26.23
t/c	0.12	0.10	0.1	0.1	0.11
AR_{ht}	4.03	4.68	4.94	4.62	3.12
λ_{ht}	0.6	0.36	0.33	0.47	0.55
Λ_{ht}	26.10	18.54	30.19	27.2	27.60
T_{Type}	1	1	0	1	1
AR_{vt}	2	2	1.8	2	2
λ_{vt}	0.73	0.494	0.32	0.32	0.53
Λ_{vt}	35	43	41.67	36.33	39
N_{eng}	2	2	2	2	2
Material	1	1	1	1	1
N_{seats}	5	5	5	5	5
l_t	74.45	74.31	70.05	68.96	71.57
S_t	226.49	200.98	205.38	220	254.4
$C_{h_{\delta e}}$	-0.22	-0.22	-0.34	-0.22	-0.22
l_v	63.90	74.04	70.88	74.73	73.22
Wo	103781	103560	103431	103970	104698
Constraint Violation %	10.65%	9.83%	10%	8.78%	9.18%

Note: Tourn. – Tournament Selection
Roul. – Roulette Selection

This scheme is used mainly to save on computing time required for the evolution of a reasonable aircraft conceptual design.

EVOLUTION OF THE AIRCRAFT DESIGN

Figures 4 through 7 below show how the top view of aircraft configuration evolves as the GA search progresses. Since the GA is a population based search the best design based on the fitness value will be selected out of the population and plotted. The design at generation's number 5, 20, 60 and 120 are presented for run 4 to illustrate the GA evolutionary design process. Note that after generation number 120 all the runs reached a steady state condition exhibiting little change in the aircraft design, since the GA has converged onto a near optimum design and is proceeding slowly to the optimum.

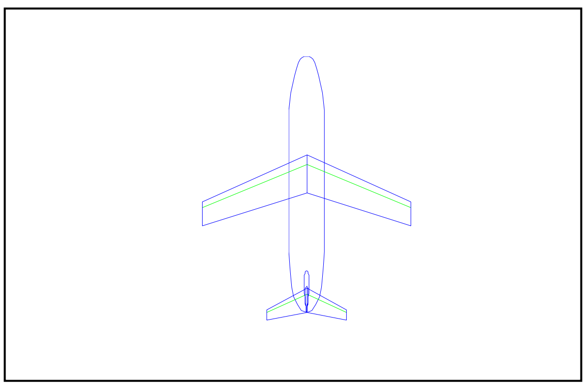


Figure 4: Best design at generation 5

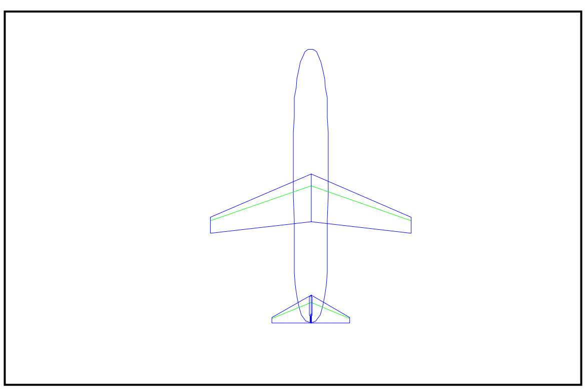


Figure 5: Best design at generation 20

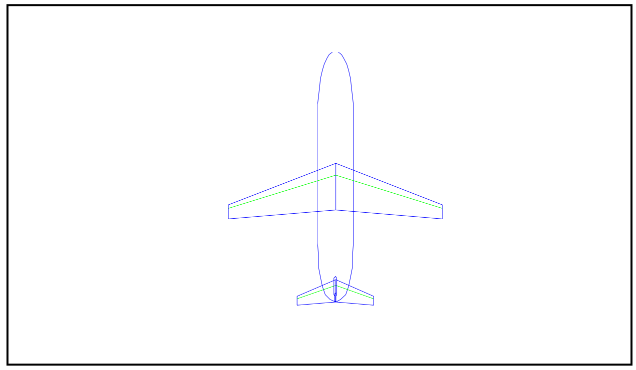


Figure 6: Best design at generation 60

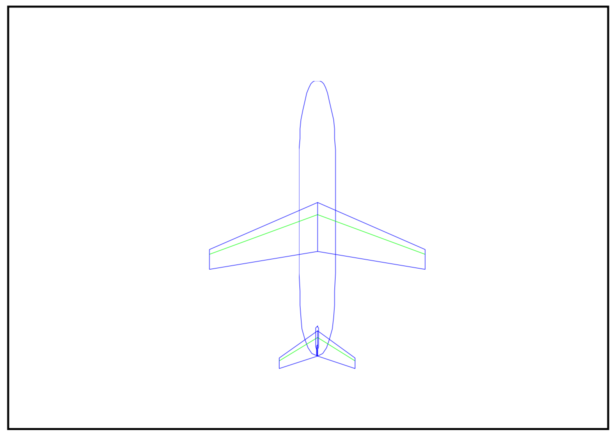


Figure 7: Best design at generation 120

Figures 4 through 7 above suggest that the GA advance from an impractical design to a conceptual aircraft design that is reasonable. In other words, the GA capability of learning is dependent on time. This fact transcends to our every day life in which our learning abilities are influence by a time factor. In addition, the evolved design coupled with reductions in constraints violation somewhat reinforces the fact that convergence towards optimal or slight optimal solutions is taking place and perhaps can be reached.

Note that even though the genetic operators used for run number 4 are not the most efficient, the GA is capable of finding a reasonable conceptual aircraft design in a small amount of time. The design in run 4 is not too efficient partly due to the selection scheme employed. Roulette selection has some undesirable properties, this is mainly because there is a tendency for a few super chromosomes to dominate the selection process; in later generations, when the population is largely converged competition between chromosomes is less strong and a random search behavior will emerge [9].

It can be argued that the design found in run number 3 is the best of the five runs since this run offers the best combination of design variables with a low weight and small constraint violation. Uniform crossover and tournament selection therefore were the most effective schemes in exploring the search space and locating the most interesting areas of this complex design space, which is the major goal of conceptual design. The reason being uniform crossover encourages the greatest amount of information exchange when compared to 1-point or 2-point crossover, while tournament selection serves a vital role of imitating mating competition in nature more closely than roulette selection.

One point and two point crossover schemes though proving useful in the aircraft conceptual design process leads to sub-optimal design due to lack of information exchange, the short generation time and to a lesser extent the small population size.
The best aircraft design layout at the end of run 4 (at generation 200) is also plotted and a graphical comparison with the existing design is indicated in figure 8. Take note of the variations in dimensions and layout of the GA evolved aircraft with the existing design.

DISCUSSION AND CONCLUSIONS

Clearly, the GA can provide a reasonable aircraft design in a short amount of time compared with the traditional design techniques. Moreover, the GA have the ability of simultaneously learning the task from all design disciplines as well as integrating the design parameters from these disciplines to arrive at efficient aircraft designs. In addition the GA was capable of handling numerous design variables, design formulations and design constraints.

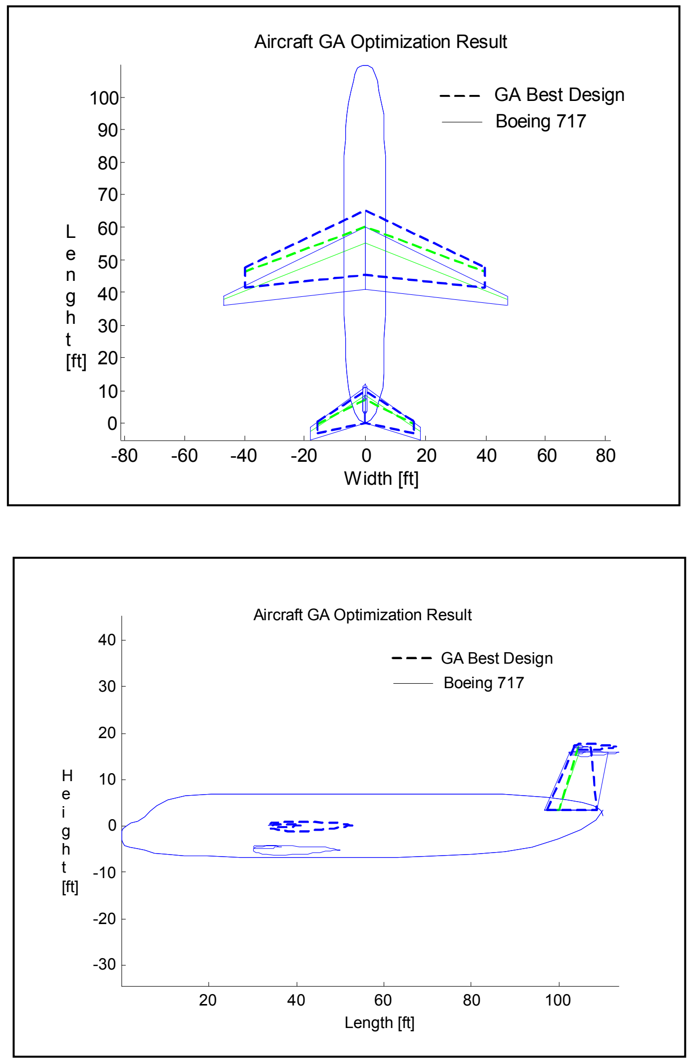


Figure 8: Top view and side view comparison of optimized aircraft found by the GA with existing design.

Hence in some ways the GA can replicate the task assign to a design team and in some cases underscore some crucial design areas that may be overlooked by a traditional design approach. On the other hand, the convergence history of the GA is slow. As a result, solutions obtained may be indicative of a simplified version of the true optimum. This is as a result of problems arising out of questions such as how large the population should be or what crossover or mutation rate to use? Or perhaps what can be done to better the GA selection process? These questions are vital since they determine the convergence quality of the GA and can play a major role in the GA decision-making.

Moreover, there is no proof of optimality with the GA generated designs since there is no gradient information available. Hence, one general limitation to the GA is the lack of simple and reliable convergence criteria. As indicated in the GA convergence history, the GA seem to get close to the optimum but takes a long time to locate this point in the search space. Thus it may be more fruitful to run several near optimum design and later combine different aspects of these various designs to achieve an optimal conceptual design.

Finally this study indicated that GAs are a flexible and efficient means of generating conceptual aircraft designs that can increase the scope and decrease the time and cost entailed in the traditional design approach.

REFERENCES

[1] Michealwicz, Z., *Genetic algorithms + data structures = Evolution*, Second Edition, Springer-Verlag, Berlin, 1994.

[2] Ruben Perez and et. al., *Aircraft Design Using Genetic Algorithm*, American Institute of Aeronautics and Astronautic, Paper No. A00-40172, Sept 2000.

[3] Coley A.D., *An introduction to genetic algorithms for Scientist and Engineers*, River Edge, New Jersey, World Scientific, 1999.

[4] Goldberg, D.E., Genetic Algorithm in Search, Optimization and Machine Learning, Addison –Wesley Reading, MA, 1989.

[5] Haupt L. R. and Haupt E. S., *Practical genetic algorithms*, New York, Wiley, 1998.

[6] Camp C. and et. al., *Optimization Design of two-dimensional structures using genetic algorithm*, Journal of structural Engineering Vol. 124 No. 5, May 1998.

[7] Crispin, Y., “Aircraft Conceptual optimization using simulated evolution,” AIAA, Paper 94-0092, January 1994.

[8] Crossley, A.W., Laananen, H.,D., “ Conceptual Design of Helicopters via Genetic Algorithm,” Journal of Aircraft, Vol. 3, No. 6, Nov.-Dec. 1996.

[9] Gen M. and Cheng R., *Genetic Algorithms & Engineering Design*, Whiley & Sons, New York, 1997.

[10] Coit D.W. and Smith A.E., *Penalty Guided Genetic search for Reliability Design Optimization*, Computers In Engineering Journal, Vol. 30, No. 4, 1996, pp. 895-904.

[11] Holland J. H., *Adaptation in Natural and Artificial Systems*, MIT Press, Cambridge, MA, 1992

[12] Raymer D. P., *Aircraft Design: A conceptual Approach*, American Institute of Aeronautics and Astronautics, Washington DC, third ed., 1999.

[13] Torenbeek E., *Synthesis of Subsonic Airplane Design*, Delft University Press and Kluwer Academic Publishers, 1990.

[14] Roshkam J., *Airplane Design,* Volumes 1-8, DARC Corporation, Ottawa, Kansas, 1998.

[15]McCormick B. W., *Aerodynamics Aeronautics and Flight Mechanics*, John Wiley and Sons Inc., Second Edition, 1995.

[16] Pamadi B. N., *Performance, Stability, Dynamics, and Control of Airplanes*, American Institute of Aeronautics and Astronautics Inc., Reston, Virginia, 1998.

[17] Stinton D., *The Design of the Aeroplane*, Blackwell Science Ltd., Great Britain, 1991.

[18] Perez R. and et. al., *Aircraft Conceptual Design using Genetic Algorithms*, Thesis report, 2000.

[19] J.Taylor, Jane’s *All the World Aircraft*, London, UK, Jane’s Yearbook, 1997 and 2000.

[20] *MATLAB’s User Guide*, The Mathworks Inc., 3 Apple Hill Drive, Natick, MA, 1999.

[21] Harik G. and et. al., *The Gambler’s Ruin Problem, Genetic Algorithms and the Sizing of Populations*, IEEE International Conference, April 1997.

[22] Koza R. J. and et. al., *Genetic Programming III*, Morgan Kaufmann Publishers, 1999.