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Research Article

Transport Aircraft Conceptual Design Optimization Using Real Coded Genetic Algorithm

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Due to soaring oil prices, increased air traffic and competition among air transport companies, and environmental concerns, aircraft maximum takeoff weight (MTOW) is becoming a critical aspect, of air transport industry. It is very important to estimate the MTOW of the aircraft in order to determine its performance. However, estimating the weight of an aircraft is not a simple task. The purpose of this paper is to present a simplified method to optimize the aircraft MTOW using a genetic algorithm approach. For the optimization of MTOW of transport aircraft, a MATLAB program consisting of genetic algorithm techniques with appropriate genetic algorithm parameters setting was developed. The objective function for the optimization was a minimization of MTOW. The use of genetic real coded algorithm (GA) as an optimization tool for an aircraft can help to reduce the number of qualitative decisions. Also, using GA approach, the time and the cost of conceptual design can considerably be reduced. The model is applicable to the air transport industry. The proposed model has been validated against the known configuration of an aircraft.

1. Introduction

Due to soaring oil prices, increased air traffic and competition among air transport companies, and environmental concerns, minimization of aircraft maximum takeoff weight (MTOW) is becoming a critical aspect, of air transport industry. Robust design of a transport aircraft is reflected in lower MTOW. Therefore, the present study considers the aircraft structural and propulsion performance for minimization of MTOW. According to Intergovernmental Panel on Climate Change projections the global passenger air travel, as measured in revenue passenger km, is projected to grow by about 5% per year between 1990 and 2015, whereas total aviation fuel use, including passenger, freight, and military, is projected to increase by 3% per year, over the same period [1]. Moreover, global aircrafts fuel consumption is expected to rise by 3% to 3.5% and reach between 461 Mt and 541 Mt in 2036. Domestic and international operations also account for 38% and 62% of global fuel consumption, respectively [2]. Literature indicates that with the increase in aviation fuel consumption the aviation emission also increases because CO_2 is proportional to aircraft fuel burn [2–5]. Chang et al. [6] pointed that the higher fuel consumption of aircrafts is one of the major causes of inefficiency of airlines. Therefore, in such a highly competitive environment, in order to reduce the environmental impact and direct operating cost of an aircraft, the aircraft MTOW optimization is essential.

In the initial design process, it is very important to estimate the MTOW of an aircraft in order to determine its performance. However, estimating the weight of an aircraft is not a simple task. Weight estimation in aircraft design is very challenging due to the high number of variables involved, and the numerous relationships between them. Liem et al. [7] employed the gradient-based methods for fuel burn minimization via multipoint aerostructural optimization. But their high development cost, noisy objective function spaces, inaccurate gradients, categorical variables, and topology optimization limit their use. Moreira et al. [8] used the analytic hierarchy process (AHP), technique in order of preference by similarity to ideal solution in fuzzy environment (TOPSIS-fuzzy), and GA in the conceptual aircraft design. However, this study does not include all parameters relevant to a MTOW optimization. Finally, Chaudhry and Ahmed [9] employed the spreadsheet based GA to aircraft preliminary

design optimization. Also, the coding in a spreadsheet environment, absence of penalty function strategies, and elitism in this study limit their use for the performance of the GA in terms of speed and best fitness. In the present study many equations of different methodologies are implemented to the aircraft different component weight estimation instead of applying one analyst's methodology.

In particular, we emphasized on GAs as a robust tool for optimization problems; several studies dealing with GAs have been developed in almost all science fields, since they can easily manage several decision variables, within different disciplines. The paper is organized as follows: first, the aircraft design problem is described and design mission profile and weight sizing module are presented; second, the optimization problem is described along with objective function and constraints; third, the GA methodology for aircraft design optimization is presented; fourth, the results of the GA optimization are reported and compared; and finally, the conclusions and implications of the study are discussed.

2. Aircraft Design Problem Description

2.1. Aircraft Design Mission. A midrange transport aircraft capable of carrying 192 passengers on domestic routes was chosen as the design to be optimized for MTOW in this study. The design mission for this aircraft may be summarized as follows:

(i) *Warmup and taxi*: warmup and taxi for 15 minutes, sea level (SL), and standard temperature.

(ii) *Takeoff*: MTOW: 72500 Kg, distance: 2110 meters, and Mach: 0.210.

(iii) *Initial climb*: initial climb to 1500 ft at 2776 ft/min and Mach: 0.336.

(iv) *1st climb:* first climb to FL 100 at 2445 ft/min and Mach: 0.380.

(v) *2nd climb*: 2nd climb to FL 350 at 958 ft/min and Mach: 0.71.

(vi) *1st cruise*: 1st cruise at FL 350, range: 800 NM, L/D: 18.5, and Mach: 0.785.

(vii) *2nd cruise*: 2nd cruise at FL 370, range: 800 NM, L/D: 18.5, and Mach: 0.785.

(viii) *3rd cruise*: 3rd cruise at FL 390, range: 800 NM, L/D: 18.5, and Mach: 0.785.

(ix) *Descent*: descent to 1500 ft at 1238 ft/min and Mach: 0.785.

(x) *Approach*: approach to 50 ft and Mach: 0.217.

(xi) *Landing*: landing to 0 ft, Mach: 0.217, and distance: 1432 m.

Figure 1 shows the aircraft design mission profile for midrange transport aircraft. This mission profile also displays constraints for the design problem. The constraints are a rate of climb greater than or equal to 2,500 ft/min, a cruise Mach number greater than or equal to 0.75, a takeoff distance of less than or equal to 8,000 feet, and a landing distance less than or equal to 6,000 feet. The objective function to be minimized is MTOW of a transport aircraft. MTOW consists of weights of several components of aircraft. It is calculated on an annual basis per aircraft in operation. The maximum takeoff weight module estimates each aircraft component weight by applying many formulae of different methodologies and trying at the same time to avoid using any formulae that have less important variables which may not be available in the early stages of aircraft design.

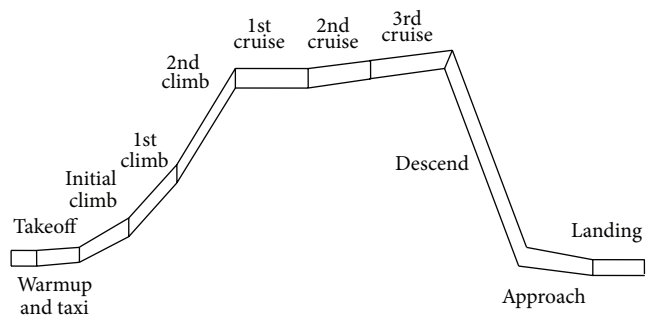

Figure 1: Aircraft design mission profile.

2.2. Weight Sizing Module. The weight module evaluates the MTOW by breaking down into the payload weight (W_{pay}), crew weight (W_{crew}), empty weight (W_e), and fuel weight (W_f). The MTOW equation is given by Al-Shamma and Ali [10] and Sadraey [11] as below:

$$W_{\text{to}} = W_{\text{crew}} + W_{\text{pay}} + W_f + W_e. \tag{1}$$

After the simplifying equation (1), both fuel weight and empty weight are expressed as fractions of the maximum takeoff weight as given below:

$$W_{\text{to}} = \frac{\left(W_{\text{crew}} + W_{\text{pay}}\right)}{\left(1 - W_f/W_{\text{to}} - W_e/W_{\text{to}}\right)}. \tag{2}$$

In (2), W_f/W_{to} is the fuel weight fraction and W_e/W_{to} is the airplane empty weight fraction. The fuel weight fraction can be calculated as the product of the weight fractions for each segment of the mission. Based upon the configuration summary, the weight fraction for taxi and takeoff (W_2/W_1), climb (W_3/W_2), descent (W_5/W_4), and landing (W_6/W_5) segments have been estimated from the historical data as suggested by Sadraey [11]. In these segments, the fuel burnt is almost nothing and negligible compared with MTOW. The segment, during which the fuel weight that is burnt is considerable, includes the cruise segment and the fuel weight fraction is W_4/W_3. Therefore, for the case of a mission with 5 segments as shown in Figure 1, the fuel weight fraction is obtained as follows:

$$\frac{W_f}{W_{\text{to}}} = \left(1 - \frac{W_6}{W_1}\right), \tag{3}$$

where W_6/W_1 can be written as

$$\frac{W_6}{W_1} = \left(\frac{W_2}{W_1}\right)\left(\frac{W_3}{W_2}\right)\left(\frac{W_4}{W_3}\right)\left(\frac{W_5}{W_4}\right)\left(\frac{W_6}{W_5}\right). \tag{4}$$

Federal Aviation Administration (FAA) regulation requires the transport aircraft to carry 20% more fuel than needed or a flight of 45 minutes to observe the airworthiness standards [11]. The extra fuel required for safety purposes is almost 5 percent of aircraft total weight, so it is applied as follows:

$$\frac{W_f}{W_{\text{to}}} = 1.05\left(1 - \frac{W_6}{W_1}\right). \tag{5}$$

The fuel weight fraction of cruise segment is determined by employing the Breguet range equation [3, 11]. Therefore, the cruise fuel weight ratio is determined as

$$\frac{W_4}{W_3} = e^{(-R\cdot C/(0.866\cdot V\cdot(\text{L/D})\max))}, \tag{6}$$

where R denotes aircraft range, C is engine specific fuel consumption, and L/D is lift to drag ratio. It is assumed that the range, cruise altitude, and velocity are fixed by the design requirements. The lift to drag ratio is taken as constant, its value is taken as 20 as given by Sadraey [11] for jet air transport. In addition, the aircraft is designed for 6 crew members and 192 passengers.

2.2.1. Empty Weight Estimation. The last term in determining maximum takeoff weight in (1) is the empty weight fraction (W_e/W_{to}). Evaluation of empty weight is done by breaking down into its components as given below. Also, as the advance composite material is used, therefore the equations for the wing weight, fuselage weight, tail weight, and nacelle group weight are multiplied by suitable fudge factors as given by Raymer [12].

Wing Weight (W_w). The wing structural weight can be estimated using wing weight equations. Wing weight represents about 17–27% of the empty weight [13]. Several levels of approximation are available. Raymer's [12] formula is selected for the reason that it gives the lowest average value, which is given as below:

$$\begin{aligned} W_w = {} & K_{\text{fw}} * \left(0.00667 * N_{\text{ult}}{}^{0.55}\right) * \left(t\_c * \text{cwr}^{-0.3}\right) \\ & * \left(\frac{b}{\cos\left(W_{\text{Sp}}/2\right)}\right)^{1.05} \\ & * \left(1 + \sqrt{\frac{1.905 * \cos\left(W_{\text{Sp}}/2\right)}{b}}\right) * \left(\frac{W_{\text{zf}}}{S_{\text{ref}}}\right)^{-0.3} \\ & * W_{\text{zf}}. \end{aligned} \tag{7}$$

Fuselage Weight (W_{fus}). Nicolai and Carichner [14] formula is used to calculate the fuselage weight as follows:

$$\begin{aligned} W_{\text{fus}} = {} & K_{\text{ff}} * 0.0737 * \left(\left(2 * D_f * V_d{}^{\wedge}0.338\right.\right. \\ & \left.\left. * L_f{}^{\wedge}0.857 * \left(W_{\text{to}} * N_{\text{ult}}\right)^{\wedge} 0.286\right)\right)^{\wedge} 1.1. \end{aligned} \tag{8}$$

Tail Weight (W_t). Torenbeek [15] formula is used to calculate the horizontal and vertical tail weight of an aircraft

$$W_t = \frac{K_{\text{ft}} * (0.051) * \left(V_d\right) * \left(S_{\text{ht}} + S_{\text{vt}}\right)^{\wedge} 1.2}{\sqrt{\left(\cos\left(W_{\text{Sp}}\right)\right)}}. \tag{9}$$

Propulsion System Weight (W_{pr_sys}). The major driver in evaluating the weight of propulsion system (propulsion and nacelle groups) is the engine dry weight. Kundu [16] suggests the following formula for estimating the propulsion system weight:

$$\begin{aligned} W_{\text{pr\_sys}} = {} & \left(6.2 * K_{\text{fna}} * n_{\text{eng}} * \text{Th}\right) \\ & + \left(1.5 * n_{\text{eng}} * W_{\text{eng}}\right). \end{aligned} \tag{10}$$

Undercarriage Weight (W_{uc}). Undercarriage size depends on an aircraft's MTOM. Mass estimation is based on a generalized approach of the undercarriage classes that demonstrate strong statistical relations, as discussed by Kundu [16]:

$$W_{\text{uc}} = 0.035 * W_{\text{to}}. \tag{11}$$

System Group Weight (W_{sys}). The systems group includes flight controls, hydraulics and pneumatics, electricals, instrumentation, avionics, and environmental controls. Kundu [16] suggests the following formula for estimating the system group weight:

$$W_{\text{sys}} = 0.1 * W_{\text{to}}. \tag{12}$$

Surface Controls Weight (W_{sur}). The weight of the surface controls is the systems associated with control surface actuation and depends mainly on the tail area; Al-Shamma [13] and Torenbeek [15] suggest the following formula related to takeoff weight instead:

$$W_{\text{sur}} = 0.4915 * W_{\text{to}}{}^{\wedge}0.666. \tag{13}$$

Furnishings Weight (W_{fur}). Furnishings are mainly proportional to the number of actual passenger seats. For more accurate calculations, this weight is based on the actual division of seats between first class and coach [13]. Torenbeek [15] formula instead depends on zero fuel weight:

$$W_{\text{fur}} = 0.196 * \left(W_{\text{zf}}{}^{\wedge}0.91\right). \tag{14}$$

Contingency Group Weight (W_{con}). Contingency group weight is calculated by using formula suggested by Kundu [16]

$$W_{\text{con}} = 0.01 * W_{\text{to}}. \tag{15}$$

Now, aircraft empty weight is the sum of all structural component weights; that is,

$$\begin{aligned} W_e = {} & W_w + W_{\text{fus}} + W_t + W_{\text{pr\_sys}} + W_{\text{uc}} + W_{\text{sur}} + W_{\text{fur}} \\ & + W_{\text{con}}. \end{aligned} \tag{16}$$

2.2.2. Operating Empty Weight (W_{oew}). This weight consists of the following subweights: operating items and flight crew weight [13]

$$W_{\text{oew}} = W_e + W_{\text{op}} + W_{\text{crew}}, \tag{17}$$

where W_{op} is operating item's weight; Torenbeek formula [15] is used for calculating operating item weight

$$W_{\text{op}} = 8.617 * Npas. \tag{18}$$

2.2.3. Zero Fuel Weight (W_{zf}). This weight consists of operating empty weight and payload [13]

$$W_{\text{zf}} = W_{\text{oew}} + W_{\text{pay}}. \tag{19}$$

3. Optimization Problem Descriptions

In this aircraft design problem, constraints were imposed on takeoff distance, rate of climb, landing distance, cruise speed, payload, and ceiling. The objective function was MTOW. The values of these functions differ by several orders of magnitude. Scaling of the variables, constraints, and objective function helps to avoid numerical and computational problems. The main purpose of this optimization procedure is to find the wing design, fuselage design, tail design, and optimized value of the engine thrust and specific fuel consumption required to minimize the total aircraft weight for the specified mission and field performance.

A single objective optimization problem to minimize MTOW was solved. The problem of minimizing MTOW as a single objective was stated as

$$\text{Minimize FF}(X) = W_{\text{to}}. \tag{20}$$

The design variables were chosen to include the key parameters for optimization in conceptual aircraft design. Nine design variables, namely, wing span (b), wing reference area (S_{ref}), wing sweep angle (W_{Sp}), fuselage length (L_f), fuselage diameter (D_f), horizontal tail area (S_{ht}), vertical tail area (S_{vt}), specific fuel consumption (C), and engine thrust (Th) for optimization were chosen as the representative set for optimization:

$$X = \left(b, S_{\text{ref}}, W_{\text{Sp}}, L_f, D_f, S_{\text{ht}}, S_{\text{vt}}, \text{Th}, C\right). \tag{21}$$

Table 1 shows the upper and lower limits of design variables. This aircraft design problem is subject to several constraints. All of the constraint functions, h^-, are negative valued when satisfied. The takeoff distance constraint equation has the form

$$h_1 = \frac{(W/S/(\sigma\,(\text{Cl})\max * T/W))}{250} - 1 \le 1, \tag{22}$$

where σ is the ratio of air density under the conditions, W/S is wing loading, T/W is thrust to weight ratio, and (Cl)max is the aircraft maximum lift coefficient in the takeoff configuration.

This uses the takeoff parameter approach to estimate takeoff field length [12]; here a value of 250 corresponds to a distance of 8,000 feet.

Table 1: Design variables and their limits and constants.

Design variable	Limits
Wing span (m)	$32 < b < 38$
Wing reference area (m^2)	$100 < S_{\text{ref}} < 150$
Wing sweep angle (degree)	$20 < W_{\text{Sp}} < 30$
Fuselage length (m)	$32 < L_f < 40$
Fuselage diameter (m)	$3 < D_f < 6$
Horizontal tail area (m^2)	$20 < S_{\text{ht}} < 30$
Vertical tail area (m^2)	$15 < S_{\text{vt}} < 25$
Specific fuel consumption (1/s)	$0.00015 < C < 0.00030$
Engine thrust (KN)	$110 < \text{Th} < 120$
Constant values	
Ultimate load factor	$N_{\text{ult}} = 4.125$
Average wing thickness ratio	$t\_c = 0.12$
Wing root chord (m)	cwr = 6.08
Maximum design speed (m/s)	$V_d = 270$
Number of engines	$n_{\text{eng}} = 2$
Engine dry weight (kg)	$W_{\text{eng}} = 2270$
Fudge factor for the wing	$K_{\text{fw}} = 0.85$
Fudge factor for the fuselage	$K_{\text{ff}} = 0.90$
Fudge factor for tail	$K_{\text{ft}} = 0.83$
Fudge factor for the nacelle	$K_{\text{fna}} = 0.90$
Aircraft range (NM)	$R = 3000$
Mach number	Mcruise = 0.785
Lift/drag ratio	(L/D) max = 18.5
Cruise altitude (ft)	Alt = 34961 to 38961
Maximum zero fuel weight (kg)	Mzf = 57275 (kg)

The cruise Mach number constraint is imposed via the following equation:

$$h_2 = 1 - \left(\frac{\text{Mcruise}}{0.75}\right) \le 1. \tag{23}$$

The minimum fuel weight (W_f) constraint is imposed via Kundu [16] weight estimation as given below:

$$h_2 = 1 - \left(\frac{W_f}{14{,}500}\right) \le 1. \tag{24}$$

A minimum rate of climb of 2,500 ft/min at sea level is also required

$$h_3 = 1 - \left(\frac{\text{Vv}}{2500}\right) \le 0, \tag{25}$$

where Vv is vertical velocity.

The constraint on landing distance uses the simple estimator presented by Raymer [12]:

$$h_4 = \frac{((80 * W/S)/\sigma\,(\text{Cl})\max + Sa)}{6{,}000} - 1 \le 1. \tag{26}$$

Here, the maximum landing distance is 6,000 feet, and Sa is the obstacle clearance distance (here 1,000 feet).

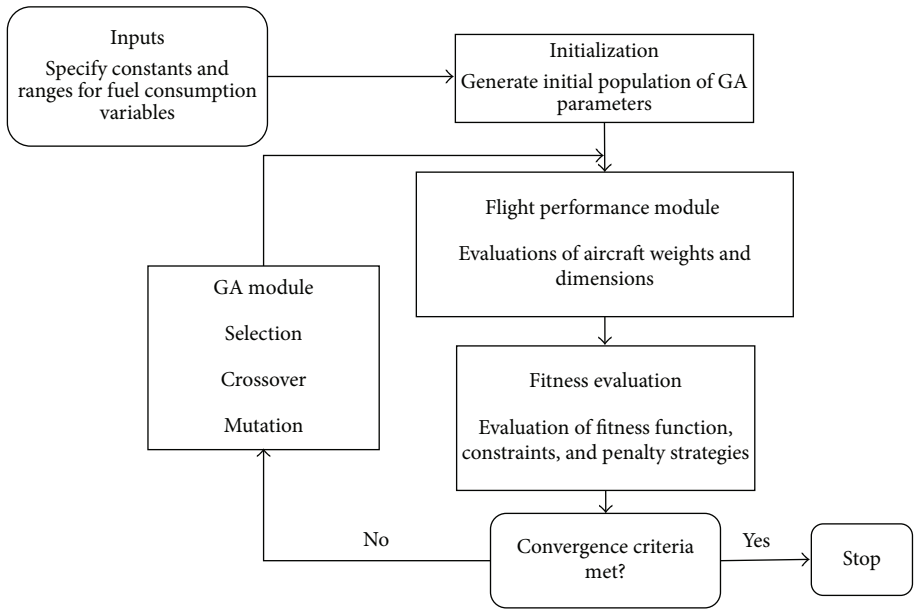

Figure 2: Flow chart of genetic algorithm.

The final constraint assures that the aircraft's ceiling exceeds the cruise altitude of 35,000 feet

$$h_5 = 1 - \left(\frac{\text{hceg}}{35{,}000}\right) \leq 0, \tag{27}$$

where hceg is ceiling altitude.

4. Methodology: GAs as an Optimization Tool for MTOW

Genetic algorithms are a class of general purpose search methods, which are particularly convenient for complex optimization problem [9]. The main concept of GA is to mimic the natural selection and the survival of the fittest [17]. The algorithm begins by initializing a population of solution; 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 [18]. The GA methods are more robust than the traditional gradient methods of optimization [19]. One of the key disadvantages of gradient-based methods using adjoints is the development cost [19, 20]. Furthermore, another potential weakness of gradient-based methods is that they are relatively intolerant of difficulties such as noisy objective function spaces, inaccurate gradients, categorical variables, and topology optimization [20]. In case of GA, development cost is minimal. Also, they are tolerant of noise in the objective function and have no difficulty with categorical variable changes [20]. In addition, GAs can explore the solution space in multiple directions at once, hence increasing the chance of finding the optimal solution [21]. Also, GA is robust in locating optimal solution and reducing the computational effort than other conventional heuristics [20]. Thus, the robustness of GA makes them an ideal candidate for aircraft design optimization.

4.1. Implementation of GA. In the present study, a GA program was developed in order to provide a genetic-based method for obtaining the optimal parameter values in transport aircraft design. For the implementation of GA, a MATLAB program consisting of around 400 lines of code was developed. The MATLAB code includes the main GA techniques with the suitable aircraft MTOW calculation methodologies. The fitness function value is passed on to the GA component as a single cell value for the evaluation of maximum takeoff weight. The developed model follows a methodological approach and the mission profile is based on the type of aircraft used for study; in this case the configuration of the aircraft was taken from the study of Chaudhry and Ahmed [9]. As shown in Figure 2, the GA evaluates the input design variables based on the aircraft weights and flight performance equations and outputs the dimensions of the aircraft and important flight performance parameters to obtain the best fitness.

4.2. Initialization. The algorithm is initialized by generating a first population of a number of individual's configurations. In the initialization, the first thing to do is to decide the coding structure. In this work the real coded GA was used. The real coded GA selection seems particularly natural when optimization problems with variables in continuous search spaces are tackled. Since real-parameters were used directly, solving real-parameter optimization problems is a step easier when compared to the binary coded GA [22]. Unlike in the binary coded GA, decision variables can be directly used to calculate the fitness values. Coding is usually described as a string of symbols from $[0, 1]$. These components of the chromosome are then labeled as genes. The number of bits that must be used to describe the parameters is problem dependent [19]. The objective function was evaluated for these individuals and the first population was produced. Typically, the initial

population of solutions is selected completely at random, with each bit of each solution having a 50% chance of taking the value 0. The second population will be generated unless we have achieved a converged solution at the first generation which is considerably weird.

4.3. Fitness and Penalizing Strategies. A fitness function is a particular type of objective function that directs the optimality of a solution in a genetic algorithm so that that particular chromosome may be ranked against all the other chromosomes. This fitness function was used to evaluate them through the selection process. But the major problem in applying a GA to the aircraft design optimization is how to handle the constraints. The constraints influence the final solution by penalizing the fitness of solutions which exceed these limits [23]. Therefore, we employed a common and efficient penalty strategy in this study. The fitness function is the product of the objective function times the penalty value. The main importance of the penalty strategy in the GA is that it unconstrained our problem by multiplying a certain penalty value to the objective function for any violation of the constraints. The multiplication with objective will have the effect of adding a certain value to our fitness value, thereby decreasing its fitness if we are minimizing. Moreover, one major advantage of the penalty strategy compared to other methods is that they never generate the infeasible solutions; instead they use these solutions in such a way to assist the search for the best solution [24]. Furthermore, another advantage that this method has over the traditional approaches is that it is problem independent [24–26]. Equation (28) shows the fitness function with penalty value.

For minimization,

$$\text{fitness} = \text{objective value} * \text{penalty value}$$

$$\text{Fitness} = \text{FF}(X) * \text{PV}(X)(1), \tag{28}$$

where $\text{FF}(X)$ is the objective value and $\text{PV}(X)$ is the penalty value:

$\text{PV}(X) = 1$ if feasible;

$\text{PV}(X) > 1$ otherwise.

The penalty value is computed using the method given by (20):

$$\text{PV}(X) = 1 + \frac{1}{n\sum_{i=1}^{n}(\Delta Vi(x)/\Delta Vi\max)^{\alpha}}, \tag{29}$$

where $\Delta Vi(x) = \max(0, \text{gi}(x))$,

$$\Delta Vi\max = \max(\varepsilon, \Delta Vi(x), x\varepsilon \mid \text{PV}(X)), \tag{30}$$

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

4.4. Selection Process and Inverse Scheme. Individual solutions were selected as parent solutions through a fitness-based process. A fitness proportionate selection known as the roulette-wheel selection was most commonly used in GA. This selection is one of the most common forms used in GA as it consistently generates high fitness solutions. The roulette-wheel selection assigns probabilities of selection depending on fitness values and the inverse scheme to scale fitness and maintains a differential between fitness values.

The inverse scheme was employed because the GA by nature optimizes via maximization; therefore the problem of changing the GA process to a minimization arises. The basic idea for the implementation of the inverse scheme comes from a simple logical deduction: the result of inverting a large number is a small number [27]. The fitness values are scaled as given by

$$\text{fsi} = \frac{F\max - (F\min/a)}{\text{fi} - (F\min/a)}, \tag{31}$$

where fsi 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 fi is the fitness values.

4.5. Crossover Operator. Crossover is the main random operator in GA and the function of the crossover operator is to generate new or "child" chromosomes from two "parent" chromosomes by combining the information extracted from the parents. The crossover operator exchanges "genes" of two parent solutions, roughly mimicking recombination between two haploid organisms between two parent solutions to form two offspring. In this study uniform crossover was employed by GA routine. In uniform crossover each gene in the offspring is created by copying the corresponding gene from one or the other parent chosen according to a random generated binary crossover mask of the same length as the chromosomes [28]. Also, the uniform crossover reduces the bias associated with the length of the binary representation used and the particular coding for a given parameter set [29].

4.6. Mutation Operator. Mutation is a background operator which produces unconstrained random changes in various chromosomes. A simple way to attain mutation would be to alter one or more genes. The mutation operator performs a random modification in binary string (0 turns 1 or 1 turns 0) that represents the design variable, thereby, allowing the recovery of some lost characteristics during the optimization process. It is an insurance policy against the irreversible loss of genetic material [28]. The mutation operator helps to create "chromosomes" by the random alteration of a bit and this allows the GA to explore more of the fitness landscape and prevent it from getting trapped in local optimal solutions. In this program, the dynamic probability of mutation is used to enhance the mutation rate at the end of the population. The dynamic probability of mutation consists in evaluating the concentration of the fitness function value in chromosomes situated close to the optimal value [29].

4.7. Elitism and Termination. In this work, the elite reservation strategy is adopted to directly copy the best individuals of the current population to the next iteration. The elite individual represents the suitable solution of the population using an elitism strategy to produce a faster convergence of the algorithm to the optimal solution of the problem. The use of elitist individual guarantees that the best fitness individual never increases (minimization problem) from one iteration to the next iteration (towards the end of the process). Elitism increases the performance of the GA in terms of speed and best fitness [30]. In the end the program is terminated after the minimum number of generations is met and the fitness value of the best solution in the generation stabilizes at a maximum such that successive iterations do not produce significantly better results.

5. GA Optimization Results

The simulation was carried out on an Intel® Core™i3-2310M CPU at 2.10 GHz computer having 4 GB RAM. For each of the run the following parameters were used: population size = 100, crossover probability = 0.80, mutation probability = 0.1, elitisms = 1, termination criteria = 200 trials, epsilon = 0.0001 (range that the fitness must change in the termination criteria), and maximum generations = 200, which corresponds to approximately 45 seconds on an Intel® Core™i3-2310M CPU at 2.10 GHz computer having 4 GB RAM.

The model was run with 9 design variables, namely, wing span, wing reference area, wing sweep angle, fuselage length, fuselage diameter, horizontal tail area, vertical tail area, specific fuel consumption, and engine thrust for optimization, 5 constraints, and 15 fixed variables shown in Table 1. The objective function was set to minimize MTOW while satisfying all of the following performance and design constraints: Mach number ≥ 0.75, takeoff field length ≤ 8000 ft, rate of climb ≥ 2500 fpm, landing field length ≤ 6000 ft, and ceiling altitude ≥ 35,000 ft. The model was verified against the study of Chaudhry and Ahmed [9] and the known configuration of various transport aircraft of commercial airlines. The actual maximum takeoff weight value and calculated value were quite close. After the validation of the model, simulations were carried out to find the optimized values of decision variables. The model was then run for 50 runs and the best fitness value was calculated, because there is no guarantee that different executions of the GA program converge to the same solution of the problem due to the stochastic nature of GA and hence the program is allowed to run 50 times to ensure the robustness of the algorithm. The best fitness value of MTOW after 50 runs was 72511 kg. The result shown in Figure 3 demonstrates the convergence of the algorithm. MTOW improves from 74,439 kg to 72511 kg, while all the constraints were satisfied. Figure 3 shows thebest and average fitness versus generation of the aircraft maximum takeoff weight. The improvement in MTOW was achieved by the reduction in aircraft operating empty weight and fuel weight. Figures 4–10 show the average and best values of wing span, wing aspect ratio, fuselage length, fuselage diameter, horizontal tail area, vertical tail area, engine specific fuel consumption, and take off thrust.

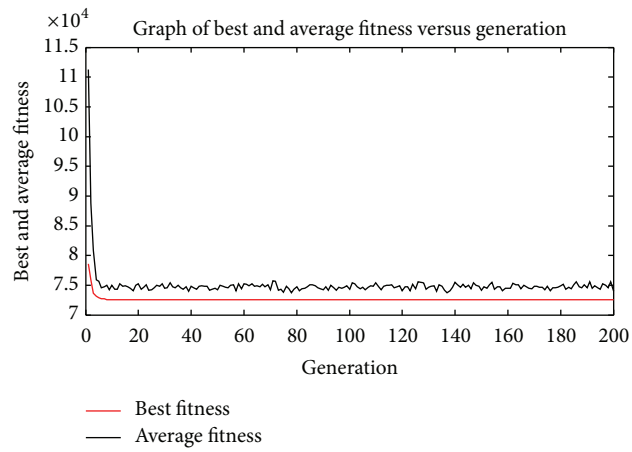

Figure 3: Best and average fitness versus generation of the aircraft maximum takeoff weight (MTOW).

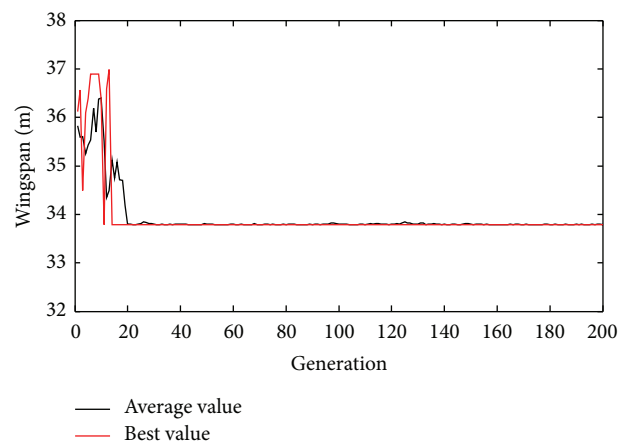

Figure 4: Best and average wingspan (m) versus generation.

In this study the wing span and wing aspect were reduced. Therefore, they yielded to a lower fuel capacity and improved fuel consumption. Moreover, it implies in higher induced drag which can lead to an inefficient aerodynamic performance due to the presence of detached flow regions over the wing. But in this study care was taken about the induced drag. So, aircraft dimensions with a compromised aspect ratio and which also considered factors such as fuel capacity, control characteristics, and size allowances were chosen. Also, the fuselage dimensions, that is, diameter and length, were optimized. Fuselage diameter was reduced because the fuselage drag is determined by the diameter of the fuselage, lowering the diameter, and lowering the drag. But reducing the drag was not only the motive behind the fuselage design. Its purpose as a payload carrier was also optimized, as the length of the fuselage was increased by keeping in mind its stability considerations. In addition, the reduction in the areas of horizontal tail and vertical tail also contributed to the improved takeoff weight value. Moreover, the use of composite material resulted in weight reduction. Therefore,

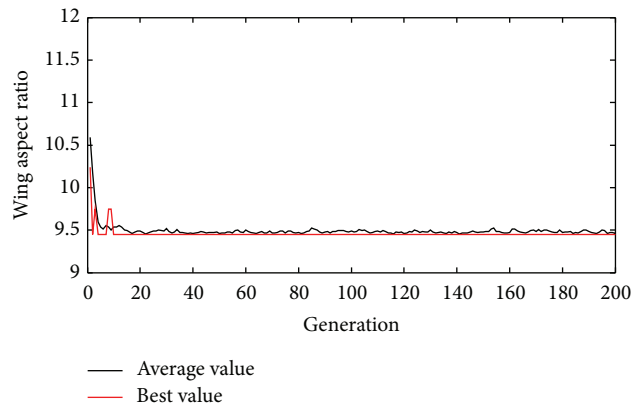

Figure 5: Best and average wing aspect ratio (m) versus generation.

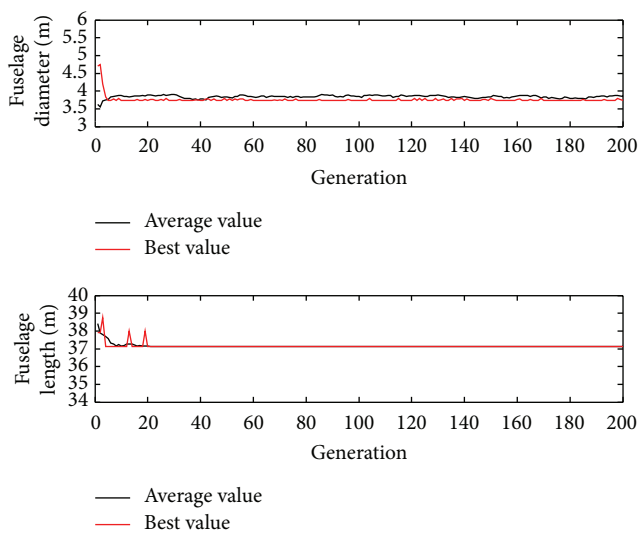

Figure 6: Best and average fuselage diameter and length (m) versus generation.

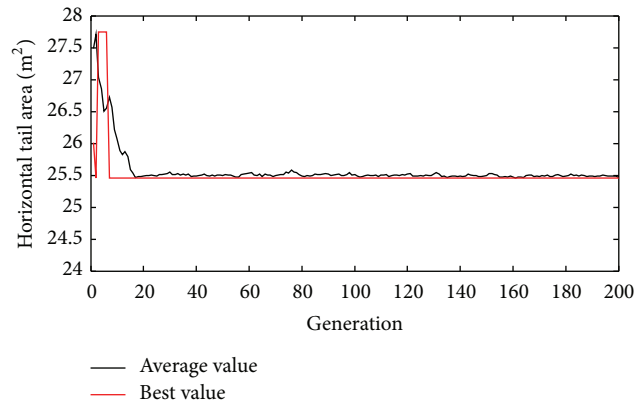

Figure 7: Best and average horizontal tail area (m^2) versus generation.

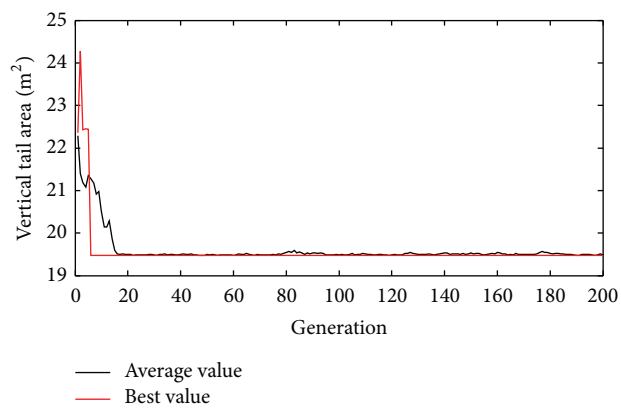

Figure 8: Best and average vertical tail area (m^2) versus generation.

it yields to a lower fuel capacity and, thereby, improved specific fuel consumption. Also, Table 2 shows the improved value of specific fuel consumption of 0.00023/s to 0.0019/s. The improvement in engine specific fuel consumption was achieved by the reduction in aircraft speed, altitude, and maximum takeoff weight. Finally, the optimized value of the engine takeoff thrust has also resulted in reduced fuel consumption.

5.1. Comparisons of Results. The model was verified against the study of Chaudhry and Ahmed [9] and the known configuration of various transport aircraft of commercial airlines. Chaudhry and Ahmed [9] had considered Airbus 320-200 for the aircraft design optimization. In this study, we have also considered Airbus 320-200 for aircraft design optimization. Therefore, results were compared with Chaudhry and Ahmed [9]. The actual maximum takeoff weight value and calculated value were quite close. After the validation of the model, simulations were carried out to find the optimized values of decision variables. Table 2 gives the comparison of different values of decision variables of developed model and the study of Chaudhry and Ahmed [9]. The comparison of the study showed that the aircraft maximum takeoff weight has been reduced from 74439 kg to 72511 kg. Therefore, 1928 kg weight reduction of MTOW was achieved.

6. Conclusions and Future Research Implications

In this paper GAs are applied to the preliminary design optimization. The results shown in Table 2 were based on a fixed probability of crossover and mutation, and a fixed population size of 100 is implemented with 200 generations used as the stopping criteria. Sometimes, a small population size causes the GA to quickly converge to a local minimum because it insufficiently samples the parameter space. In addition, elitism strategy is employed to prevent the loss of a potentially better solution by ensuring that its presence is maintained in the population at every generation until an even better solution is located. Specifically, the analyzed study confirms that the use of evolutionary optimization algorithm is useful for evaluating the potential improvements in aircraft fuel consumption as well as preliminary design. Finally, it can be concluded that optimization performed by the MATLAB

Table 2: Comparisons of the optimized values of decision variable.

Variable name	Developed model values	Chaudhry and Ahmed [9], calculated values for Airbus A320-200	Eurocontrol data base [31]
Maximum takeoff weight (kg)	72,511	74,439	73,900
Wing span (m)	33.80	38	34.10
Wing aspect ratio	9.45	10	
Wing reference area (m^2)	120.89	—	
Wing sweep angle (degree)	25	25	
Horizontal tail span (m)	12.07	15.30	
Horizontal tail area (m^2)	25.47	—	
Horizontal tail aspect ratio	5.72	—	
Vertical tail span (m)	6.01	6.12	
Vertical tail area (m^2)	19.47	—	
Vertical tail aspect ratio	2.19	—	
Fuselage length (m)	37.12	36.58	37.57
Fuselage diameter (m)	3.75	4.572	
Engine thrust (KN)	114.50	—	111–118
Range (Km)	5,556	5330	
Specific fuel consumption (1/s)	0.00019	0.00023	
Number of passengers	192	195	180
Mach number	0.785	0.79	
Cruise altitude (m)	10,668	11229	12,497
Operating empty weight (kg)	38,681	—	
Wing weight (kg)	6,171		
Fuselage weight (kg)	7,773		
Tail weight (kg)	1,104		
Propulsion system weight (kg)	8,087		
Undercarriage weight (kg)	2,537		
System group weight (kg)	7,250		
Surface controls weight (kg)	848		
Furnishing weight (kg)	4,222		
Contingency group weight (kg)	725		
Zero fuel weight (kg)	54,414		
Payload weight (kg)	15,744		
Fuel weight (kg)	15,950		

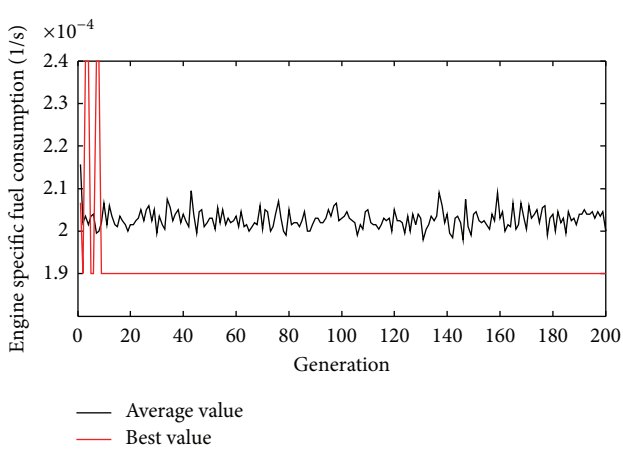

Figure 9: Best and average engine specific fuel consumption (1/s) versus generation.

coded GA has given better result than the spreadsheet coded based GA.

Further, this work can be implemented for any of aircrafts without disturbing the logic of GA routine, thus making it a general purpose solution approach. In this study, only the maximum aircraft takeoff weight had minimized, in the future maximization of lift over drag, and minimization of MTOW can be performed simultaneously. The variable aircraft range, cruise speed, wing root chord, engine dry weight, and lift over drag ratio, which were taken as constants, can also be varied according to flight performance and design conditions. At last, genetic algorithms have been recognized by several researchers as the most promising techniques for FCO and aircraft design optimization. But when the populations have a lot of subjects, there is no absolute assurance that a genetic algorithm will find a global optimum. Other types of population based optimizers should also be

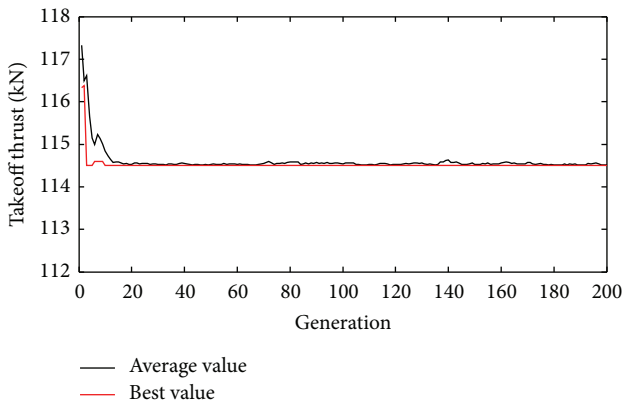

Figure 10: Best and average takeoff thrust (KN) versus generation.

researched such as particle swarm optimization (PSO), ant colony optimization (ACO), and bee colony optimization (BCO) and compared to both binary and real genetic algorithms for aircraft design optimization applications.

Competing Interests

The authors declare that there are no competing interests regarding the publication of this paper.

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