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Wing Optimization for High Endurance Applications Using Teaching Learning Based Optimization

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Abstract

The advancement in the field of aerospace has increased manifold over the past 4 decades with UAV design optimization being no exception. UAV Design and Optimization is a game of compromise. We cannot obtain a design which is best in each and every aspect. Over the years people have been using natured inspired algorithms to solve design optimization problems. This paper presents the application of a new advanced algorithm – Teaching Learning Based Optimization for optimizing wing of an Unmanned Aerial Vehicle for High Endurance applications. The results of this single objective problem are obtained taking four parameters i.e. aspect ratio, taper ratio, maximum thickness to chord ratio and maximum lift coefficient as design variables and an attempt has been made to understand the efficiency and robustness of TLBO over GA – the most widely used aircraft design optimizer.

NOMENCLATURE

α	angle of attack
AR	Aspect ratio
b	span
C_D	Total Drag coefficient
C_{D0}	Parasite Drag coefficient
C_{Di}	Induced Drag coefficient
C_l	Lift coefficient
C_m	Pitching moment coefficient
C_{mac}	Mean aerodynamic chord
e	Oswald's efficiency factor
λ	taper ratio
ρ	density of air
S_W	Wing Area
t/c	thickness to chord ratio
V_S	Stall velocity

INTRODUCTION

Aircraft design and optimization is a complex process where the design team is presented with a problem that takes inputs from various disciplines such as aerodynamics, structures and propulsion. But since these disciplines are inter-linked the existence of a design which is best in every aspect is not possible. There has to be a trade-off between various objectives or disciplines to obtain the optimum design that suits the desired purpose.

Even with the increase in complexity in design problems, the enthusiasm of the researchers did not decrease and they have worked on varied problems ranging from single-objective problem of wing design to multi-disciplinary design taking conflicting disciplines like aerodynamics and structures into account. Turnbull[1] very remarkably explained a methodology for conceptual sizing of UAVs for a specific mission, by using simple calculations to estimate aerodynamic coefficients and performance parameters during each segment of the flight. Rajagopal[2] formulated a MDO problem by coupling aerodynamic and structural analysis and concluded that when a Kriging model was incorporated in the optimization loop, the computational time was reduced. Dineshkumar[3] summarized that in most cases the optimum configuration obtained after multi-criteria optimization with wing span and stall velocity as two conflicting variables has lowest aspect ratio, highest thickness and smallest aircraft length.

This problem proceeds like a conventional optimization problem by choosing a baseline model (by performing analysis in XFLR5), then using an appropriate optimizer for attaining the desired result. Over the years, researchers have worked on various methods for optimization and shared their results for helping new generation researchers and design experts. Arora and Mauler[4] presented an elaborative list of methods and categorized all the optimization techniques into three categories – Prior, Post and No articulation preferences. Marta[5] addresses the effect of various GA parameters on the efficiency of the algorithm using aircraft design problems. After studying Truncated Newton (gradient based) algorithm, direct search method and GA, Clayton et al[6] concluded that direct search approach requires lesser number of evaluations than GA but with increasing number of variables the GA proves to be more efficient and robust. Based on all these considerations GA was chosen as the base optimizer for comparison. But since all the evolutionary and swarm intelligence based algorithms require controlling parameters like population size, no. of generations etc. the need arose for an algorithm that did not require any algorithm-specific control parameter. The need was fulfilled with the development of Teaching Learning Based Optimization by Dr. R. Venkata Rao.

Though researchers have been using TLBO for optimizing problem in various fields, full realization of TLBO potential in Aircraft design problems is yet incomplete. Kaur S.[7] has used TLBO for optimizing the design of a poly-phase filter for up-sampling of audio signals. Rao and Kayankar[8] have proved the effectiveness of TLBO over other algorithms by taking a multi-objective problem of Process parameter optimization in a multi-pass turning process operation. Tiwari A.[9] used TLBO for scheduling of reactive power control variables for voltage stability enhancement as it proved to be an efficient method for finding global solutions to large scale non-linear optimization problems.

The problem uses four wing parameters namely Aspect ratio (AR), Taper ratio (λ), max. thickness to chord ratio and maximum lift coefficient as design variables for single objective problem of UAV endurance optimization for 3 hours. Section 2 describes the baseline model realization and Section 3 highlights optimization using TLBO followed by Results, Conclusions and References.

PRELIMINARY DESIGN PROCESS

Problem statement

The objective of this project was to “design an Unmanned Aerial Vehicle which has an average endurance of 3 hours” keeping in mind the following constraints:

1) Should be portable and able to fit in a box dimension of 1.5mx1.5m.

2) Span constraint between 2meters to 4.5 meters

3) Maximum take-off weight 8 kg (includes 3 kg payload).

4) Should be stable and be able to withstand gust.

5) Should have very good performance characteristics.

Aerofoil Selection

The design process started off with study of aerofoil from different databases available, the aerodynamic behavior of different aerofoils were studied and compared from the wind-tunnel results available. Eight aerofoils like Selig-S-1223, Eppler 420, Clark-Y, FX 63-137sm, Cr 001sm and NACA 2412 etc. were chosen for comparison.

The analysis of different aerofoils was carried out using open source software XFLR5 which uses panel analysis method and XFOIL codes written by Mark Drela of MIT. The analysis was carried out at a Reynolds Number 300,000. The aerofoils were compared on four parameters - C_l/C_d vs α, C_l vs α, C_l vs C_d and C_m vs α and FX 63-137sm was chosen to be the best aerofoil.

Geometry Selection

It was decided to make another matrix analysis to determine the best wing shape, wing and tail-plane geometry for the desired design taking into consideration all the performance characteristics and parameters intended to be obtained. A scale from 1 to 5 was used to grade each wing shape with 1 being least favorable and 5 being most favorable.

After an exhaustive research, monoplane high-wing rectangular configuration was chosen and for empennage conventional configuration was chosen.

Design Calculations

Design calculations were performed and parameters like aspect ratio, wing span, wing chord, tail dimensions were obtained which were then incorporated in XFLR5 and analysis was performed. Similar trials were run by varying the speed, span, chord and moment arm length; tabulated and the best design was chosen. Dimensional parameters are given in Table 1 and characteristic curves in Fig. 1-4.

Table 1: Dimensional parameters of the best design

Velocity	16 m/s
Wing Area	0.879 sq. m
Aspect Ratio	10
Span	2.96 m
MAC	29.7 cm
Reynolds Number	316,696
VHT	0.606
Moment arm length	1.5 m
Horizontal stab Area	0.1402 sq. m
Horizontal stab span	64.8 cm
Horizontal stab chord	21.7 cm
Vertical Stab Area	0.0826 sq. m
Vertical Stab Span	35.3 cm
Vertical Stab C_{root}	31.2 cm
Vertical Stab C_{tip}	15.6 cm

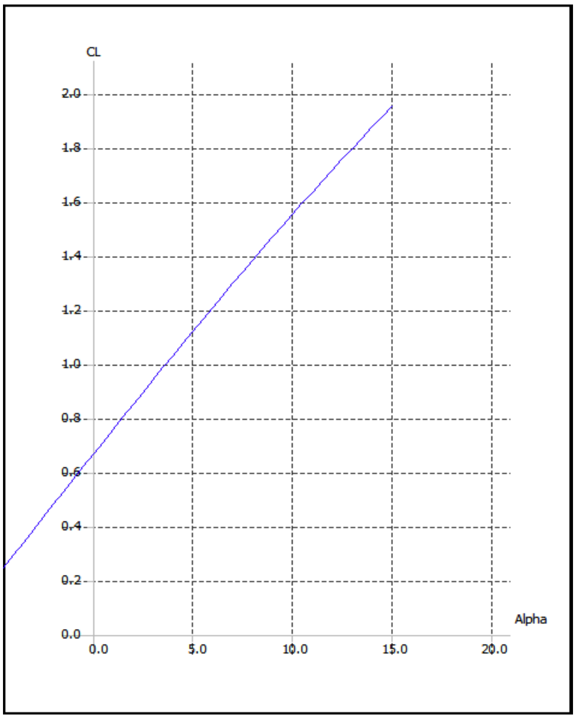

Figure 1: C_L variation with α

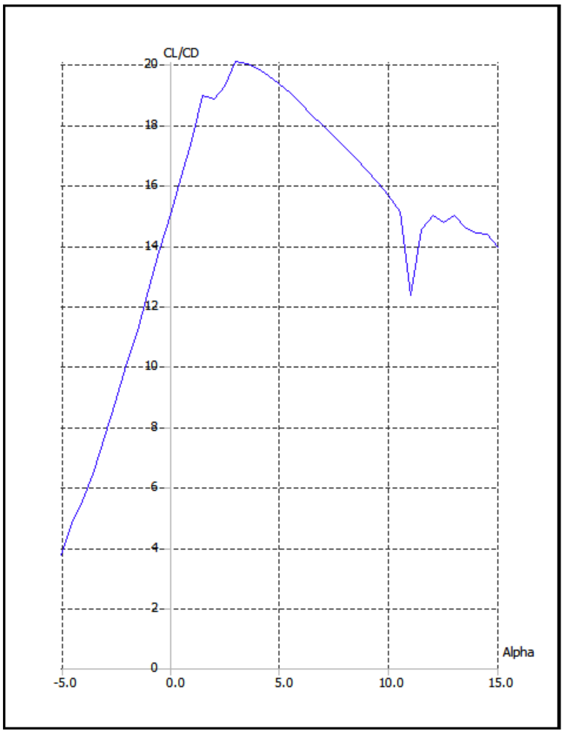

Figure 2: C_L/C_D variation with α

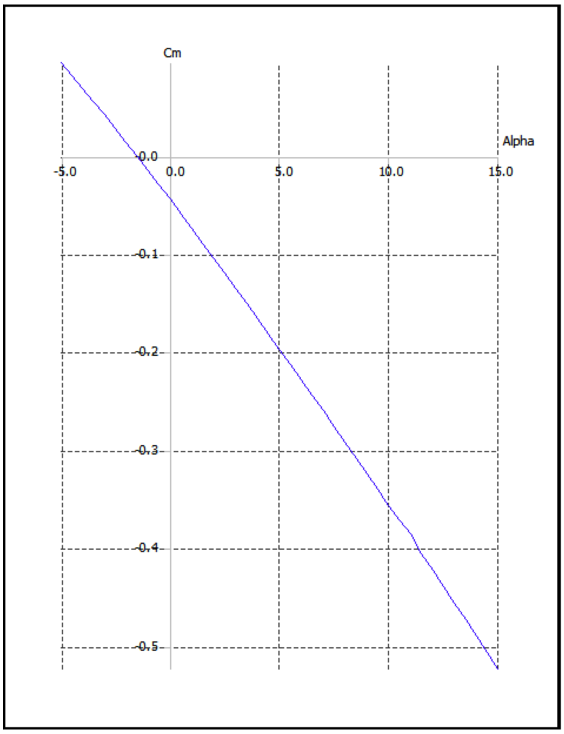

Figure 3: C_m variation with α

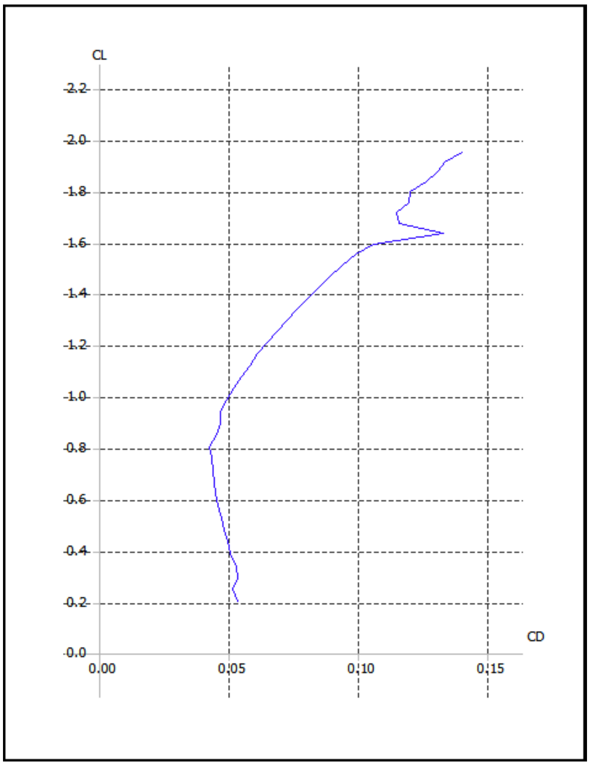

Figure 4: Variation of C_L with C_D

OPTIMIZATION OF THE UAV DESIGN

The objective function – Endurance

In general, the objective functions are identified from the design mission of the aircraft. The objective function to be maximized in the current work is Endurance. Endurance is the measure of time the aircraft can spend in cruising flight. It is directly proportional $C_L^{3/2}$ / C_D. Also it is inversely proportional to power required. The lower the value of power required the higher is the value of endurance.

The mathematical model

The UAV chosen in the current work is a propeller driven aircraft but since it is battery operated, there is no change in the weight during the flight. Hence, the standard formula for endurance (given below) is not applicable in the current case[10].

$$E = \frac{\eta}{c}\sqrt{2\rho S}\,\frac{C_L^{3/2}}{C_D}\left(W_1^{-1/2} - W_0^{-1/2}\right) \quad (1)$$

For battery operated UAVs, Wagner et al [11] computed a formula for Endurance which is:

$$E = \frac{E_b * N_m * N_p * M_b}{(\rho * S_W * [(V_S)^3] * C_D) * 9.81} \quad (2)$$

Where,

E_b = Battery Density

N_m = Efficiency of the motor

N_p = Propeller Efficiency

M_b = Mass of battery

V_s = Stall Velocity

Mathematical Calculations:

1) Area required:

$$S_W = \frac{2W}{\rho * Cl_o * V_o^2} \quad (3)$$

2) Span:

$$b = \sqrt{AR * S_W} \quad (4)$$

3) Mean Aerodynamic Chord:

$$C_{mac} = \frac{0.75 * S_W * (1+\lambda)^2}{b * (1+\lambda+\lambda^2)} \quad (5)$$

4) Stall Speed:

$$V_s = \sqrt{\frac{2W}{\rho S_W C_L}} \quad (6)$$

5) Drag Coefficient of Wing:

$$FF = \left[1 + \frac{0.6}{(x/c)\max}\left(\frac{t}{c}\right) + 100\left(\frac{t}{c}\right)^4\right]\left[1.34M^{0.18}(\cos\Lambda)^{0.28}\right] \quad (7)$$

$C_{Do} = C_{f,c} * FF_c * Q * S_{wet,c} / S_{ref}$ (8)

$C_{Di} = C_L^2 / (\pi.e.AR)$ (9)

C_D for wing = $C_{Do} + C_{Di}$ (10)

Variables

In order to satisfy the mission design requirement, various wing planform parameters are considered as design variables. The aspect ratio, taper ratio, thickness to chord ratio and $(C_L)_{max}$ are the wing parameters treated as design variables. The upper and lower bounds for the wing planform are indicated in Table 2. Throughout this project, the variables are kept same as actual and no normalization (i.e. presenting as ratios with respect to the maximum value) is done as it increases computational time.

Table 2: Design variables - Lower and Upper bounds

	Lower Bound	**Upper Bound**
Aspect Ratio	5	15
Taper Ratio	0.2	1
Thick./Chord ratio	0.07	0.12
Max. Lift Coefficient	1.2	2.3

Constraints

The constraints are imposed on cruise velocity, air density and efficiencies of motor and propeller etc. These performance constraints arise again from the requirements and all the constraints are constant and tabulated in Table 3.

Table 3: Equality Constraints

V_o	18 m/s
E_b	200
N_m	0.85
N_p	0.85
ρ	1.1 kg/m^3
W	78.48 N
M_b	3 kg

Optimizer

In the following section the optimization techniques are discussed elaborately. In this paper one of the oldest and most generalized optimization technique - GA has been used for comparing the efficiency and robustness of a new technique – TLBO over itself. These are discussed below in detail:

Genetic Algorithms [12]

Genetic Algorithm is one of the oldest and most successful optimization technique based on Nature of evolution. It was originally proposed by John Holland in the 1960's at the University of Michigan, to study the process of evolution and adaption occurring in nature. These algorithms work on the basis of Darwinian evolutionary theory, involving mechanisms such as selection, inheritance, crossover and mutation. To start the computation, a group of solutions (population) are randomly initialized. Each solution "chromosome" consists of a string of "genes" that represent the input design variables to be optimized.

The first operation i.e. "Selection" is inspired by the principle of 'Survival of the Fittest'. The search begins from a randomly generated population that evolves over successive generations (iterations). Based on the design variable values, each solution is evaluated via the objective function, which imposes penalties if critical constraints are exceeded, and assigned a fitness value. This fitness value is used to evaluate them through the selection process.

The second operation is the "crossover" operation which is inspired by mating in biological populations. The parent solutions undergo crossover – recombination of chromosomes to produce offspring. The crossover operator exchanges "genes" of two parent solutions, roughly mimicking recombination between two haploid (single chromosome) organisms between two parent solutions to form two offspring.

The third operation is mutation which causes diversity in population characteristics. It causes local modifications to the new generations randomly. Repeat selection, crossover and mutation operations to produce more new solution until the population size of the new generation is same as that of the old one. The iteration then starts from the new population. Since better solutions have a larger probability to be selected for crossover and the new solution produced carry the features of their parents, it is hoped that the new generation will be better than the old one 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.

TLBO [13]

Population based algorithms which are mainly nature inspired and which simulates different natural phenomena to solve a wide range of problems are popular in research fields. The Teaching–learning-based optimization technique is a recently proposed room. TLBO is a teaching–learning process-inspired algorithm proposed by Rao et al. [16] based on the influence of a teacher on the output of learners in a class. TLBO is a population based optimization method. In this optimization algorithm, a group of learners is considered as a population and different subjects offered to the learners are considered as different design variables, of the optimization problem. A learner's result is analogous to the "fitness" value of the optimization problem. The best solution in the entire population is considered as the teacher. The terms used as design variables are represented as the parameters involved in the objective function of the given optimization problem and the best solution is the best value of the objective function.

The algorithm describes the teaching–learning ability of the teacher and learners in a classroom. The teacher and learners are the two vital components of the algorithm. This algorithm is divided in two basic modes of the learning:

- Through teacher (known as the teacher phase)
- Interacting with the other learners (known as the learner phase)

Teacher Phase: In this step the teacher increases the mean result of the class in subjects taught in the class depending on his/her capability. In our case, we need to find set of students having maximum marks representing the filter coefficients. At i number of iterations, assume there are m number of design variables, the values of [a, b] which are two in n number of learners (i.e. population size) in a class, which is the size of matrix [row x column], representing marks matrix which is based on order of the filter final marks or coefficients that are extracted. The difference between the existing mean result of each subject and result of the teacher for each subject is given by:

$$\text{Difference\_Mean}_{j,k,i} = r_i(X_{j,kbest,i} - T_F M_{j,i}) \qquad (11)$$

Where, $X_{j,kbest,i}$ is the result of the best learner (i.e. teacher) in subject j. T_F is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range [0, 1].

Value of T_F can be either 1 or 2 and is decided randomly with equal probability as:

$$T_F = \text{round}\ [1+\text{rand}(0,1)\{2-1\}] \qquad (12)$$

Based on the $\text{Difference\_Mean}_{j,k,i}$, the existing solution is updated in the teacher phase according to the following expression:

$$X'_{j,k,i} = X_{j,k,i} + \text{Difference\_Mean}_{j,k,i}, \qquad (13)$$

Where $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$. Accept $X'_{j,k,i}$ if it gives better function value. All the accepted function values at the end of the teacher phase are maintained and these values become the input to the learner phase. The learner phase depends upon the teacher phase as explained in next step.

Learner Phase: In this phase the interaction of learners with one another takes place. The process of mutual interaction tends to increase the knowledge of the learner. The random interaction among the learners improves his/her knowledge. Considering a population size of n, the learning phenomenon of this phase is expressed below.

Randomly select two learners P and Q such that $X'_{total-P,i} \neq X'_{total-Q,i}$ (where, $X'_{total-P,i}$ and $X'_{total-Q,i}$) are the updated values of $X_{total-P,i}$ and $X_{total-Q,i}$ respectively at the end of teacher phase)

$$X''_{j,P,i} = X'_{j,P,i} + r_i\ (X'_{j,P,i} - X'_{j,Q,i}),\ \text{If}\ X'_{total-P,i} < X'_{total-Q,i} \quad (14)$$

$$X''_{j,P,i} = X'_{j,P,i} + r_i\ (X'_{j,Q,i} - X'_{j,P,i}),\ \text{If}\ X'_{total-Q,i} < X'_{total-P,i} \quad (15)$$

Accept $X''_{j,P,i}$ if it gives a better function value.

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RESULTS AND DISCUSSION

An in house MATLAB code was developed to optimize the wing for maximum endurance using TLBO and base algorithm GA. The ambient conditions and other constant parameters like density of air, cruise velocity, Cl_o, C_{Lmax} etc. were input. Comparison between the GA model and TLBO is tabulated in Table 4 and the salient features are discussed below:

1. The results of GA and TLBO are quite similar, the value of fitness function being slightly greater.
2. TLBO takes less computational time as compared to our baseline optimizer GA.
3. The value of t/c ratio and C_{lmax} obtained in both the cases is same.

One point that needs to be kept in mind is that the problem considered in this case in not complex i.e. it is single objective taking only four design variables. Better comparison can be obtained by making the problem more complex by considering multiple objectives or even multiple disciplines like aerodynamics and structures etc.

Table 4: Comparison of TLBO with GA

	TLBO	**GA**
AR	15.00	14.407
λ	0.579	0.403
t/C ratio	0.07	0.07
C_{lmax}	1.2	1.2
S_W	0.6033 sq. m	0.6033 sq. m
b	3.008 m	2.948 m
C_{mac}	19.59 cm	19.3 cm
V_S	9.5578 m/s	9.5578 m/s
C_D	0.04695	0.04821
E	3.248 hours	3.1634 hours

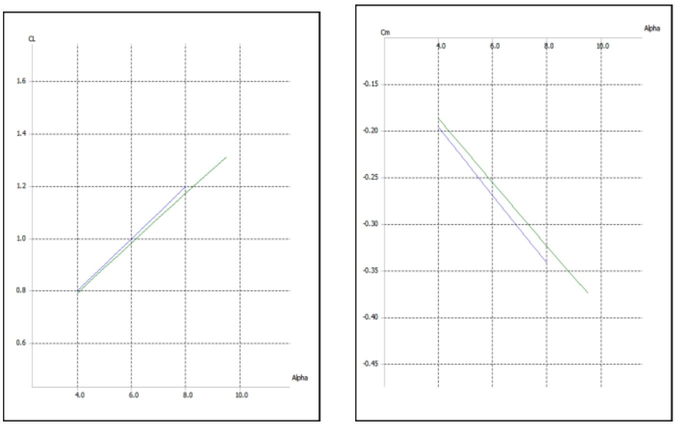

Figure 5: C_{Lmax} vs α and C_m vs α for GA(green) and TLBO(blue)

CONCLUSION

Maximization of endurance was carried out by optimizing wing parameters using Teaching Learning Based Optimization. The results show that maximum Endurance is attained for high aspect ratio, low t/c ratio and high C_{lmax} values.

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