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Multi-Objective Aerodynamic Optimization of a Civil Aircraft Fuselage

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Abstract

In this work, a multi-objective optimization is applied for shape design of a civil aircraft fuselage. Basically, a fuselage is not designed to generate the lift but, its drag force is so important for reducing the flight cost. Thus, the fuselage is normally designed for minimum drag. However, its minimum drag is usually obtained at a very low (or even negative) angle of attack in which the lift force is also close to zero or being negative. Hence, an attractive objective would be to optimize the shape of the fuselage so that it has the minimum drag while obtaining the positive lift. In fact, a multi-objective solution is required in this case. The solution of Reynolds Averaged Navier Stokes equations is used for the calculation of aerodynamic coefficients. A new body shape parameterization method is used that is able to generate a variety of possible geometries in a regular manner. Proper limitations are defined to accommodate sufficient space for passengers and their baggage. Another important issue is to let the incidence angle being variable in order to find its best value. The fuselage of the 150+ seat civil aircraft designed in the Amirkabir University of Technology is used as initial geometry. The result show that by optimizing the fuselage geometry and incidence angle at cruise conditions, the drag coefficient is reduced by 22% while the lift coefficient is increased from -0.4406 to +0.0494.

Keywords: Genetic algorithm, aerodynamic optimization, civil aircraft fuselage, fuselage geometric parametrization, numerical flow solution

1. Introduction

On most airplanes, the body plays a fundamental role in placing the wing, tail assembly, landing gear, and propulsion system in their proper positions. Some investigations are done in structural weight optimization of fuselage and its acoustics [1]. Also, there is a brief survey of the aerodynamic conditions of the fuselage in [2, 3]. A fuselage could produce 30 percent of the drag force in aircraft [4]. Hence, decreasing the fuselage drag coefficient can reduce the cost of the flight significantly.
Researches are carried out studying the effect of the angle of attack on the aerodynamic coefficients of the fuselage [3]. In another study, Nicolosi et al. simulated the flow to predict the fuselage's aerodynamic coefficients [4]. Aerodynamic coefficients of the fuselage have also been examined on the different positions of the wing connected to the fuselage [5]. Various methods are used to reduce the drag coefficient of the fuselage. One of these methods is controlling the return flow by using the vortex generator in sensitive areas [6]. Kota et al. reported that a one-percent reduction in the drag will save about $140 million of fuel cost annually [7].
Among different optimization methods, Genetic Algorithm (GA) have been widely used by researchers since they are very efficient in finding the global optimum for complex functions [8]. It is one of the most powerful methods that can solve various optimization problems, especially where the objective function is stochastic, discontinuous, non-differentiable, or highly nonlinear [9].
Three dimensional view is usually considered for aerodynamic shape design optimization. However, this approach requires significant amount of computational cost. Another way that has been applied to optimize the aircraft wing is to optimize its two-dimensional cross-section [10, 11]. The fuselage side-view plays the main role in aerodynamic and dictated by some well-known structural and cabin space design rules. Thus, by using only fuselage side-view parameterization, it is possible to optimize the complete fuselage geometry. In the present work, the fuselage is optimized by considering its side-view, as it has the main effect on the flow around it. To achieve this goal a parametrizing procedure is used and the 150+ seat aircraft fuselage is optimized. The Genetic algorithm is used for optimization and the angle of attack is also considered as variable.

2. Design Optimization by Genetic Algorithm

Genetic algorithms are a class of stochastic optimization algorithms inspired by biological evolution [12]. For many optimum design problems, it is desirable to achieve, if possible, the simultaneous optimization of multiple objectives [13]. These objectives, however, are usually conflicting, preventing simultaneous optimization of each objective [14]. Therefore, instead of searching for a single optimal solution, a multi-objective genetic algorithm is necessary to find a set of optimal solutions (generally known as Pareto-optimal solutions). In this study, the MOGA algorithm is used to find the Pareto-optimal solutions to the fuselage optimization problem [14].

3. Parameterization of the fuselage

Considering minimum parameters is one of the main features of the fuselage parametrization. The geometry of the fuselage should generate with quality and continuity. Three different curves were used to parameterize the nose. Use one curve to create the tip of the nose, and by changing the position of the circle center and the radius, this part of the nose can change. Two different curves, which are also a branch of a large circle, have been used to model the lower and upper parts of the fuselage nose. For parameterization of the middle section, two parallel horizontal lines of variable lengths have been considered. There two parallel lines have a fixed distance, and the distance between them has been determined according to the minimum height required for passengers and the load section. Also, two different curves and two lines create the tail section. A straight line with a variable length extends the bottom of the fuselage tail, which makes an angle with the horizon. This angle is one of the significant parameters for the fuselage structure. Similarly, the lower and upper parts of the fuselage tail are modeled with two curves. Figure 1 shows the parameterization of the fuselage.

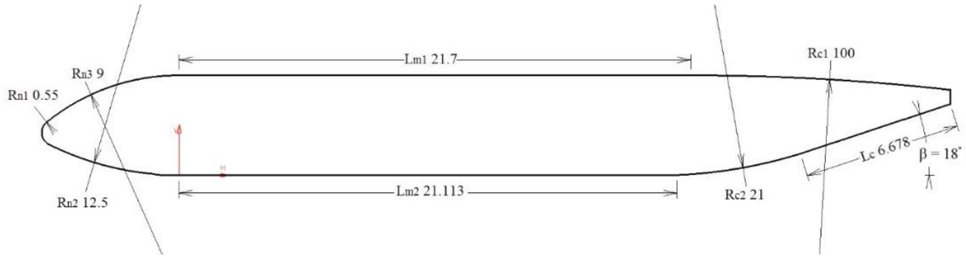


Figure 1 – View of the fuselage.

The values of the original side view of the initial fuselage are as follows in Table 1.

Table 1 – Parameters used for fuselage shape optimization in GA.

parameters	R_{n1}	R_{n2}	R_{n3}	L_{m1}	L_{m2}	R_{c1}	R_{c2}	L_c	β
Amounts	0.55m	12.5m	9m	21.7m	21.113m	100m	21m	6.678m	18^0

For the optimization process, it is necessary to determine the bound of each proposed parameter. The range for each parameter is presented in Table 2.

Table 2 – Boundary of parameters used for fuselage shape optimization in GA.

parameters	R_{n1}	R_{n2}	R_{n3}	L_{m1}	L_{m2}	R_{c1}	R_{c2}	L_c	β	α
Bottom Boundaries	0.3m	10m	6m	19.53m	18.22m	80m	12m	6.01m	15^0	0
Top Boundaries	0.8m	15m	12m	23.78m	24m	120m	30m	7.34m	21^0	3

4. The optimization process

This section presents the optimization process of the fuselage by using the Genetic Algorithm(GA). An optimization process is done by coupling different softwares such as ANSYS direct optimization, Design Modeler, ANSYS Meshing, and ANSYS Fluent, as shown in Figure 2.

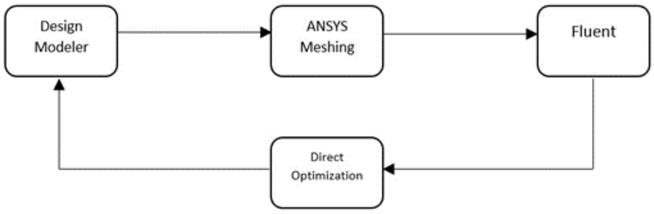


Figure 2 – Information flow in the Optimization process.

All individuals of GA have been represented by parameters, which generate the fuselage shape through the Design Modeler. In the next step, a suitable mesh is generated around the fuselage shape by the grid generation software, which creates a 2D mesh as an input to the CFD solver. The flow solver should calculate the flow field for given flow conditions and report the lift coefficient Cl and the drag coefficient Cd, which are used to calculate the objective values for a given fuselage shape. Finally, the objective values for all shapes in a generation are considered to create a next generation of the fuselage, and the process is repeated to obtain the Pareto front following the GA procedure. From the Pareto front, the optimal solution is selected. The fuselage shape that corresponds to the optimal objective value is the final shape of the optimized fuselage.

4.1 Implementation of MOGA

The ANSYS Direct Optimization software is used for implementation of the MOGA. We choose 50 individuals (fuselages) for each generation. The crossover and mutation rates are set to 0.98, and 0.01 respectively. Two objective functions considered for this multi-objective optimization. The first objective is to minimize Cd, and the second objective is to maximize Cl. The fuselage shape that corresponds to the optimal objective values is the final shape of the optimized fuselage.

4.2 Shape Generation

The ANSYS Design Modeler software was used to generate fuselage shapes. First of all, the necesary parameters are introduced as inputs to this software to create new geometry. Based on the parameterization method described in section 3, the new geometry of the fuselage is generated in this part.

4.3 Mesh Generation

ANSYS Meshing is considered to generate unstructured mesh around the 2D fuselage. The shape generated in the Design Modeler is loaded into ANSYS Meshing to create a mesh around the fuselage. For generated cells, determining a suitable element's size on the fuselage and the first layer thickness in the boundary layer cells is crucial. To improve the quality and density of the mesh around the fuselage, the growth rate of cells is 1.1.

The length of the 2D fuselage model is equal to its actual length (38.5 m), and the size of the element on the fuselage can control the mesh quality. The height of the first layer element in any mesh is fixed for considering a y+ value of less than 40. The thickness of the first layer is 0.0003 m in the boundary layer, and 15 cells have been created in the boundary layer. Mesh independency is examined by establishing different meshes as reported in the following table.

Table 3 – Grid independency results.

Mesh	Number of cells	Lift coefficient	Drag coefficient
coarse	7.5×10^3	-0.4171	0.0325
medium	1.8×10^4	-0.4406	0.0308
fine	2.43×10^4	-0.4395	0.0307

Results show that the variation in lift coefficient and drag coefficient on the medium and fine meshes are small. Therefore, the medium mesh was selected for calculating the objective functions, which can provide computational efficiency with acceptable accuracy. Figure 5 shows the medium mesh around the original fuselage.

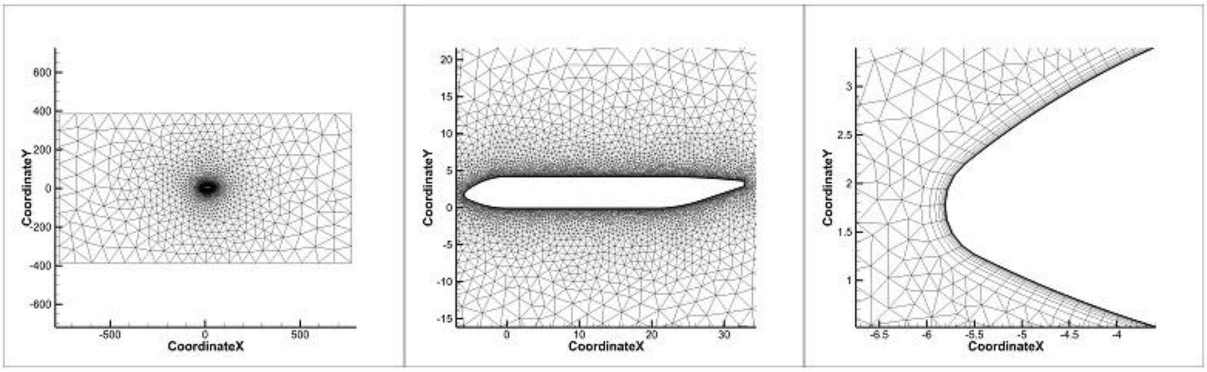


Figure 3 – The medium mesh around the original fuselage.

4.4 Flow Field Computations

The flow around the fuselage is computed by solving the compressible RANS equations with the k-ε turbulence model. The equations are solved by the finite-volume method. The convection terms and diffusion terms are discretized with the second-order upwind schemes. Also, the density-based scheme is used assuming the air as ideal-gas. The boundary conditions for simulation were based on the aircraft's flight altitude. Mach number is 0.75 (257.4 m/s), Re= 278 million, the temperature is 224 K, and Far-field pressure is 26500 Pa. The convergence criterion for any 2D simulation is the reduction of residuals from 1 to 5×10-4.

5. Results and Discussion

5.1 Validation

RAE2822 airfoil which is a transonic airfoil, has been considered for validation. Its experimental data are available for comparison with calculated results [15]. The flow conditions and boundary conditions for validation have been based on the experimental data. Mach number is 0.73, Reynolds number 6.5×106, angles of attack 2.80 degree, temperature 300 K, and far-field pressure 10^5 Pa.

As shown in Figure 6, comparing the results shows that there is a fair distribution of pressure from numerical results with experimental data.

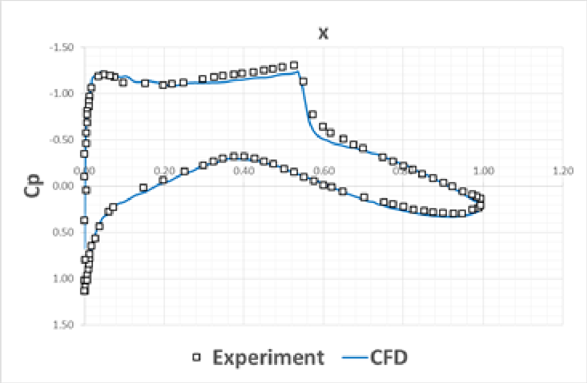


Figure 4 – Surface pressure coefficients for the RAE2822 airfoil.

5.2 Optimization Results

There are results of optimizing the fuselage shape with a variable angle of attack (AOA). The results show different candidate shapes, which are presented in Figure 5.

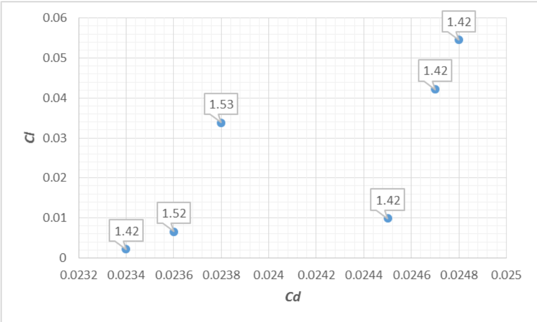
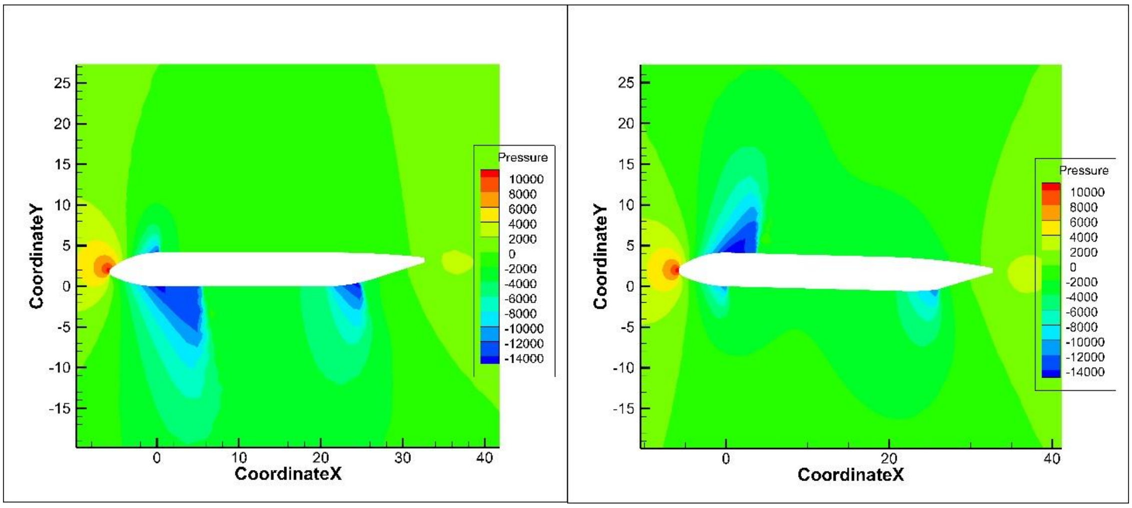


Figure 5 – Lift and drag coefficients of MOGA optimization candidates with variable AOA.

The candidate point with the third lower drag coefficient was selected as the optimum result since it has a relatively higher lift coefficient in comparison with the two other shapes with lower drag coefficient. As shown in this figure, the candidate chosen has 1.53-degree AOA. Table 4 shows the comparison of results between the original and the optimum fuselages. The results show that the optimum body has 22.4% less drag coefficient and 111% more lift coefficient than the original geometry. The optimum angle of attack is 1.53 degree.The pressure contours around the original and the optimum geometry are demonstrated in Figure 6.

Table 4 – Comparison of the results for the original and multi-objective optimum fuselage.

	Cd	*Cl*	*Cl / Cd*	*α*
Original fuselage	0.0307	-0.4406	-14.33	0
Multi objective optimum fuselage	0.0238	0.0494	2.07	1.53
Percentage improvement	22.4 %	111 %	114 %	-



a) Original body b) Optimum body

Figure 6 – Comparison of pressure contours.

6. Conclusions

Multi-objective shape optimization of the civil aircraft fuselage is carried out. The optimization process performed to reduce the drag coefficient and increase the lift coefficient significantly. Based on the results, the drag coefficient was decreased by 22.4 percent, and the lift coefficient was increased by 111 percent in comparison with the original shape. The lift-to-drag ratio improved by 114 percent. The results show that the optimization method was efficient and could optimize the fuselage and save the computational cost significantly.

Copyright Statement

References

[1] van Tooren, M. and L. Krakers. *Multi-disciplinary design of aircraft fuselage structures*. in *45th AIAA Aerospace Sciences Meeting and Exhibit*. 2007.

[2] FIRMS, I.C., *International Journal of Research in Advent Technology.* International Journal, 2014. **2**(1).

[3] Welstead, J., B. Reitz, and G. Crouse. *Modeling Fuselage Aerodynamic Effects in Aircraft Design Optimization*. in *50th AIAA Aerospace Sciences Meeting including the New Horizons Forum and Aerospace Exposition*. 2012.

[4] Nicolosi, F., et al., *Fuselage aerodynamic prediction methods.* Aerospace Science and Technology, 2016. **55**: p. 332-343.

[5] Della Vecchia, P. and F. Nicolosi, *Aerodynamic guidelines in the design and optimization of new regional turboprop aircraft.* Aerospace Science and Technology, 2014. **38**: p. 88-104.

[6] Mattos, B., R. Papa, and L.C. Santos. *Considerations about forward fuselage aerodynamic design of a transport aircraft*. in *42nd AIAA Aerospace Sciences Meeting and Exhibit*. 2004.

[7] Kota, S., et al. *Mission adaptive compliant wing–design, fabrication and flight test*. in *RTO Applied Vehicle Technology Panel (AVT) Symposium*. 2009.

[8] Holland, J.H., *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*. 1992: MIT press.

[9] Gen, M. and R. Cheng, *Genetic algorithms and engineering optimization*. Vol. 7. 1999: John Wiley & Sons.

[10] Shahrokhi, A., A. Jahangirian, and N. Fouladi. *Navier–Stokes optimization using genetic algorithm and a flexible parametric airfoil method*. in *ERCOFTAC Conference on Design Optimization: Methods and Application, University of Las Palmas de Gran Canaria, Spain*. 2006.

[11] Shahrokhi, A. and A. Jahangirian, *A surrogate assisted evolutionary optimization method with application to the transonic airfoil design.* Engineering Optimization, 2010. **42**(6): p. 497-515

[12] Goldberg, D.E., *Genetic algorithms in search.* Optimization and MachineLearning, 1989.

[13] Srinivas, N. and K. Deb, *Muiltiobjective optimization using nondominated sorting in genetic algorithms.* Evolutionary computation, 1994. **2**(3): p. 221-248.

[14] Konak, A., D.W. Coit, and A.E. Smith, *Multi-objective optimization using genetic algorithms: A tutorial.* Reliability Engineering & System Safety, 2006. **91**(9): p. 992-1007.

[15] Dillmann, A., et al., *New Results in Numerical and Experimental Fluid Mechanics VII: Contributions to the 16th STAB/DGLR Symposium Aachen, Germany 2008*. Vol. 112. 2010: Springer Science & Business Media.