Airfoil Shape Optimization for a Formula One Car Front Wing Using Multi-Objective Genetic Algorithm

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A multi-objective evolutionary algorithm (MOEA) optimization code is applied for the design of a low speed airfoil section for the front wing of a Formula One car in the ground effect regime. Design objectives are specifically targeted at maximizing down-force and minimizing the change in down-force over a range of heights. Adhering to these design objectives ensures an increase in cornering speed, stability, and improved handling of the car. The NSGA-II multi-objective genetic algorithm is applied to a potential flow solver to determine the global Pareto front. The PARSEC shape parameterization model constitutes the design variables in the optimization process. Sample routines are presented in this paper to demonstrate the robustness of the optimization procedure.

I. Introduction

Formula one racing is a very passionate sport around the world and especially Australia where a major Grand prix event is held in Albert Park, Melbourne. From a company and racing perspective, the passion is generated through fierce competition between the engineers behind the design of the car. Performance primarily depended on engine, tires, suspension, and most importantly the driver. In recent years, however Formula One design has deviated away from the usual automotive components and has increasingly begun to focus on aerodynamic design. Knowledge and understanding of the ground effect phenomenon has led to the design and application of inverted wings to Formula One cars for improved handling and stability. The competition in the formula one racing industry is fierce and even a „small' advantage over their competitor will be crucial. In recent years, focus of performance is shifted dynamically on down-force. Utilizing an aerodynamically streamlined profile acts as a major contribution to the total down-force generated. The new generation of Formula One racing will depend on the amalgamation of aerodynamic design principles to evolutionary optimization algorithms.

In order to apply the optimization technique, first it is important to understand the technical difficulties of Formula One racing with regards to design. The ability to negotiate a corner has been a major hurdle. With modern engine technology available today, a stalemate for maximum velocity is transpired. Therefore an upper hand to a fast cornering velocity may determine the fate of the final result. It is also significant to note that FORMULA ONE cars have virtually no height tolerance due to the proximity of the ground and little if any ability to handle bumps and curbs. Bumps and other track unevenness will cause the height of the front wing to change. It is observed from results obtained of parametric studies of wings by Carrese[3] Soso[4] and Ranzenbach[9] in ground effect that a slight alteration in height may produce large fluctuations in the force coefficients. In terms of race conditions, a disruption to the height would cause wicked instability and unfavorable behavior. A major concern would be the loss of velocity or uncharacteristic vibrations. With the contributing factors described above, two design points will be targeted for optimization. It is argued in this research that maximizing down-force and minimizing the derivative of down-force over height will increase the performance significantly. Maximizing the down-force will provide a faster cornering velocity. Minimizing the derivative will increase the stability and handling over curbs and unpredictable bumps.

An airfoil Optimization procedure requires three key stages: airfoil parameterization, aerodynamic solver, and the optimization technique. The role of airfoil shape parameterization is to select a mathematical representation of the airfoil geometry through a number of shape variables. An 11 parameter PARSEC method allows for strict control over the airfoil geometry, and has proven in Sobieczky[5] to conform to a wide variety of shapes. The PARSEC method has been also been incorporated elsewhere for optimization studies: Shahrokhi[6], Hajek[7].

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The validity and convergence of the final Pareto front heavily depends on the accuracy of the aerodynamic solver. For optimization purposes, the flow solver must provide an accurate representation of the flow field, without large computationally expense. A potential flow solver AEROWIG[15] has been selected due to the complexity of the conditions and the ability for a fast computation time. Since the objective functions target the evaluation of down-force, inviscid assumptions have been applied. A future consideration is to apply Reynolds-Averaged Navier Stokes (RANS) to investigate the viscous effects.

Evolutionary algorithms (EA) have received much focus in aerodynamic design over gradient based optimization methods due to their ability in determining the global optimum from candidate solutions especially for multi objective purposes. EA techniques perform a global search and are not sensitive to premature convergence as a result of local minima, which often occurs in aerodynamic design problems. EA mimics evolutionary biology through selection, reproduction and mutation of candidate solutions. The sub-class Genetic Algorithm (GA) has received wider attention from aerodynamic designers. The population-based feature of these algorithms promotes global convergence for discrete, continuous and non-differentiable functions described by Arora[1]. A multi-objective NSGA-II[2] is selected based on the formality of the objective functions and low computational requirements.

The paper is organized as follows: Section II-A the Parsec method and the boundaries of the PARSEC variables that will be predicted for Formula One application. Section II-B comprises of the flow solver AEROWIG as a valid solver in ground effect. Section II-C introduces MO-GA and its algorithm NSGA-II to the fitting of Formula One optimization. The sample routines are presented in section III. Our focus is to obtain global Pareto front and intelligently selects and optimum set of a PARSEC airfoil coordinates with respect to Formula One Application.

II. Algorithm

A. PARSEC parameterization

A full PARSEC method is an eleven design parameter airfoil generator, as shown in Fig.1. Described in a parameterization study by Shahrokhi[6], PARSEC method is one of the most effective methods for airfoil representation in the design optimization field. The airfoil is represented by a linear combination of shape functions up to a 5th degree polynomial function:

$$Z_K = \sum_{n=1}^{6} a_{n,k} X_K^{n-1/2} \tag{1}$$

The airfoil will be divided into 5 sections, consisting of leading edge, two upper sections, and two lower sections split by $\boldsymbol{x_{up}}$ and x_{lo} respectively. The leading edge section is simply defined by parameter r_{LE}. The aim is to determine the shape factors in Eq.(1) for each the other four section and the coordinates (Z, X) will be formed accordingly. To determine the shape factors, six boundary conditions (BC) will be given for each section consisting of end points for the section as well as the respective 1st and 2nd derivatives with respect to X. The BC will depend on the defined eleven parameters. Applying the BC to Eq.(1) and its 1st and 2nd derivative, a system of six independent equations is created along with the six unknown shape factors for each section.

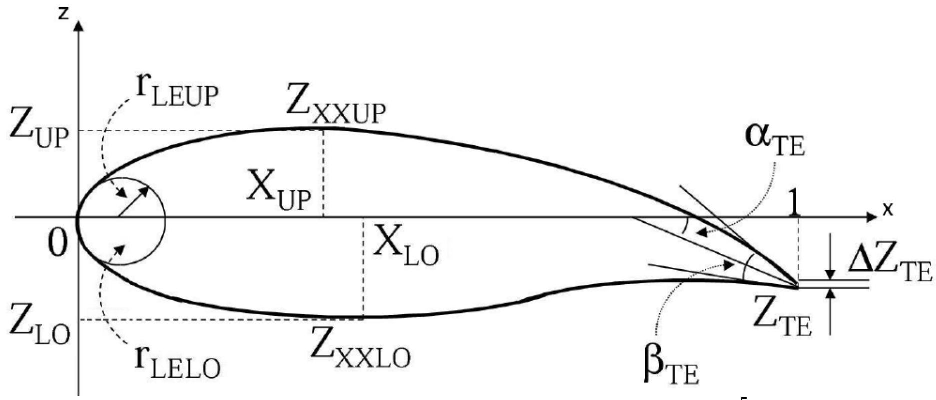

Figure 1. Design parameters for PARSEC shape functions[5]

With the control of 11 parameters, it is viable to generate all possible airfoil shapes. A vital area to link the optimization problem with the Formula One application is the selection bounded constraints on the airfoil. It is essential to select the constraints within FIA regulations[10] and desired race conditions. Two autonomous constraints must be incorporated; fixed angle of attack and fixed height above the ground. For race conditions, a very low Cm is desired for good stability. Cm will be fixed at 0.6. With the bounded constraints in Formula One application, only ten parameters will be used, omitting the trailing edge thickness Δ_{TE}. The variable is fixed at 0.

Not all the airfoil shapes is applicable to formula 1 racing. Airfoil section for Formula One application will depend on the racing conditions and airfoils that produce the desired aerodynamic properties to maximize the performance. A low fidelity potential flow solver is used as a means to select the parameter ranges. The Parsec method is used to conform to a series of typical low Reynolds number airfoils such as NACA, Eppler, Drela, Clark and Gottigen Airfoil series cumulated from UIUC[8]. Upon conforming to these airfoils, the potential flow solver is used to estimate the fitness landscape, as shown in Fig. 2.

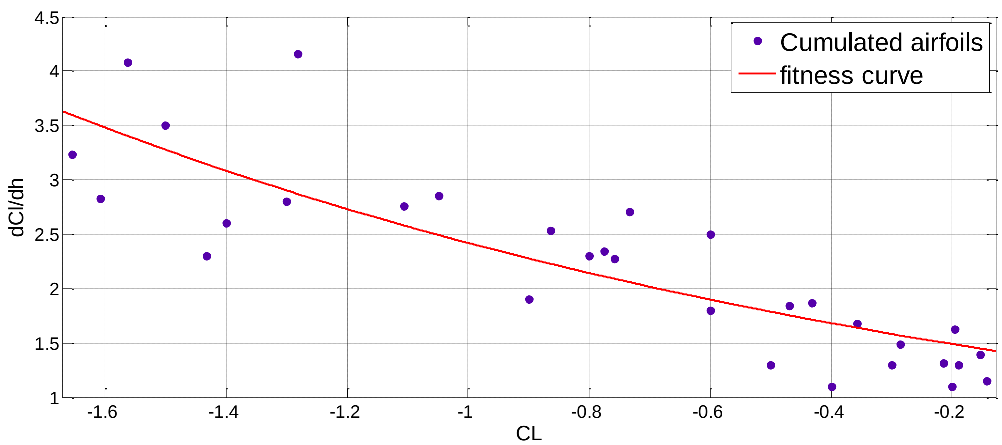

Figure A. Cumulated airfoils plotted against the objective parameters

Fig.2 shows an even spread indicating that the boundaries for the parsec variables allow for a large variation in fitness space. The ability to converge to the Pareto optimal set will primarily depend on the cluster of initial population of points. The large variation and even spacing will maintain an even distribution of the improved population points of the global Pareto front.

It is important to illustrate that the 9 parameters of PARSEC method is capable of producing a fitting shape of the selected airfoils. A least square shape fitting tool in Matlab is used to obtain the desired parameters for the selected airfoils with examples shown in Fig.3.

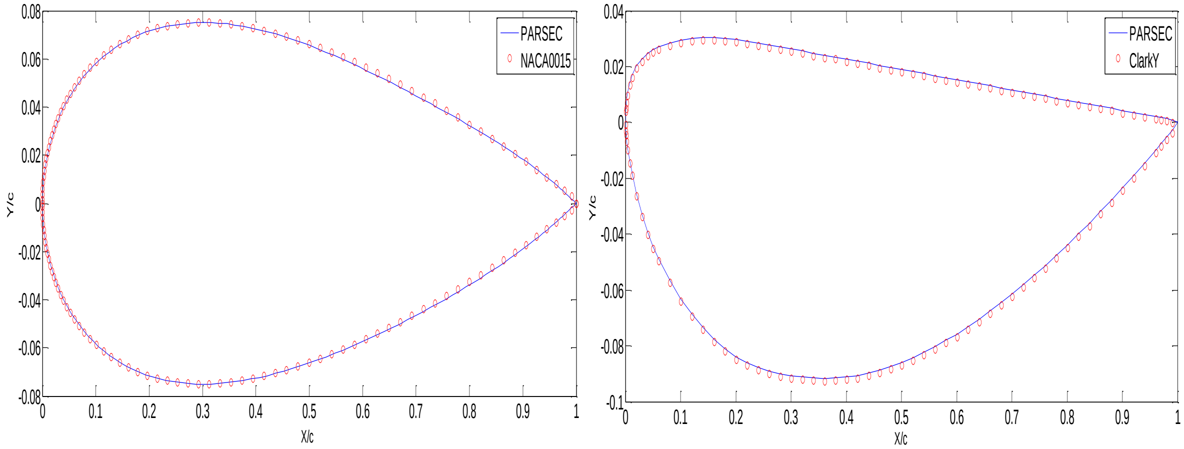

Figure 3. Airfoil shape fitting using Matlab Least Square curve fitting

An intelligent selection of bounded constraints of PARSEC parameters is primarily dependent on the most outer and inner bounds from the cumulated airfoils series. It was observed that shape fitting posed a major problem with Low Reynolds number airfoils such as Drela and Eppler. The position of x_{lo} of such airfoils was in the proximity of the leading edge and caused conflicts with the leading edge radius and therefore must be readjusted to suit the shape fitting. The lower bound of x_{lo} was adjusted from 0.05 to 0.2. The constraints are summarized in table 1

Table 1. Bounded constraints on PARSEC variables

Parameter	Bounds
r_{LE}	$[0.00335, 0.252]$
x_{up}	$[0.3, 0.41]$
z_{up}	$[0.0042, 0.135]$
x_{lo}	$[0.2, 0.38]$
z_{lo}	$[-0.076, -0.03]$
$z_{xx,up}$	$[-0.912, -0.225]$
$z_{xx,lo}$	$[0.05, 0.8]$
α_{TE}	$[-0.25, -0.02]$
β_{TE}	$[0.02, 0.215]$
Z_{TE}	$[-0.02, 0.02]$

B. Inviscid potential flow solver

The output of the flow solver will be inviscid lift coefficient and its gradient with respect to h/c. AEROWIG[15] is a potential flow solver developed in Matlab using 2nd order vortex panel method coupled with PARSEC method targeting analysis of an inverted airfoil in ground effect. In a study of Caresse[3], AEROWIG accurately captured the behavior of aerodynamic properties in the proximity of the ground. An inverted NACA 4412 and 0015 is tested in ground effect using AEROWIG and compared to experimental results found in Ranzenbach[6]. The experimental results gathered comprises of viscous effect of a Re number of 1.5 million tested using a Glen L. Martin wind tunnel. Note: h/c is the ground clearance (distance from minimum thickness of the airfoil to the ground) over the chord.

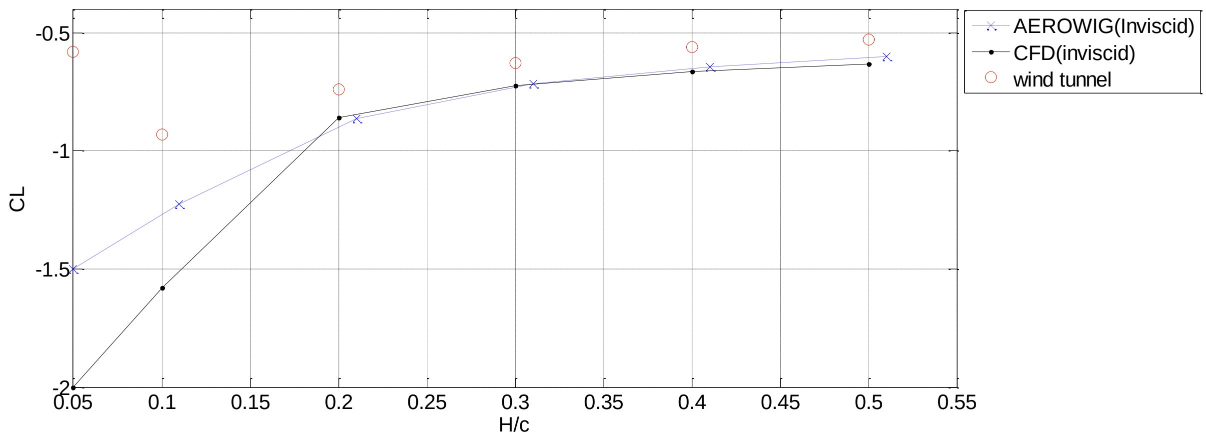

Figure 4. Comparison of an inverted NACA 4412 in ground effect at zero Angle of Attack

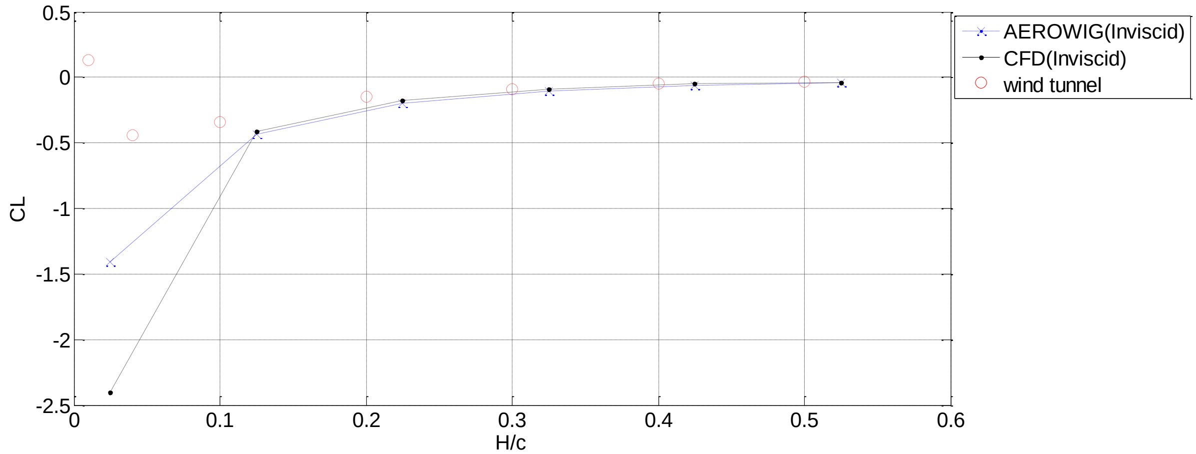

Figure 5. Comparison of an inverted NACA 0015 in ground effect at zero Angle of Attack

Fig.4-5 demonstrates AEROWIG agrees with experimental results for a h/c above 0.2 with the exception of 10-15% discrepancy. The error range is expected considering the comparison is between viscous and inviscid flow. However the trend of correlation is agreeable above a h/c of 0.2. Below this value, viscous effects dominate as our potential flow solver may not be applicable within this range. Results obtained from a third comparison using finite volume Fluent computational fluid dynamic (CFD) solver, reinforces AEROWIG as an accurate solver in ground effect without the expense of computation time. The objective function of maximizing down-force at a fixed ground clearance of approximately 0.3c (specified by FIA[10]) will obtain a valid result. However the respective derivative will be strictly limited to a range above 0.2. A future consideration is to apply Reynolds-Averaged Navier Stokes (RANS) to investigate the viscous effects between the ground and a h/c of 0.2. This will allow a more practical anatomy of the application.

C. Multi objective Genetic algorithm: NSGA-II

The knowledge of GA for a single objective optimization is extended to provide an effective approach for solving MO problems. The approach is to combine information from previous iterations to evaluate and improve a population of points (bounded PARSEC parameters for Formula One based airfoils) rather than a single point at a time. A global Pareto front represents the cluster of optimal points. In general, MO GA is divided into subclasses for selection of designs for the next generation.

The applied algorithm: NSGA-II, proposed by Deb et al[2], is based on a non-dominated sorting approach using the Elitist strategy. With the non-dominated sorting strategy, individuals that are not dominated by any other are assigned to the first front with rank 1. Those who are dominated only by one and two individuals are assigned to the second (rank 2) and third front (rank 3) respectively. The process is carried out until all individuals are assigned the rank.

The algorithm uses binary tournament selection where two individual chromosomes are randomly selected and their fitness (rank) is compared. The individual with better fitness is selected as a parent chromosome to fill a mating pool. A parameter called *crowding distance* is used to estimate a density of solutions around a particular individual. The crowding parameter of individual x is the average side-length of the cuboid enclosing individual x without including any other point in the population. When both selected individuals have the same fitness level or rank, the individual with higher crowding parameter is preferred. In other words, the individual in a lesser crowed region is selected. This crowding distance is also used as a determinant in the non-dominated sorting phase to sort individuals from the same front.

III. Sample Routine

The bi-objective test problems are selected from a number of significant past studies in Zitzler, Deb and Thiele[12], Deb[13] and Kursawe[14] to demonstrate the convergent capability of the algorithm. All sample routines are run for a maximum of 500 generations and with a population size of 50. The crossover probability of 0.9 and mutation probability of 1/n (n is a number of design variables in each test function). Crossover and mutation distribution indices are both 20.

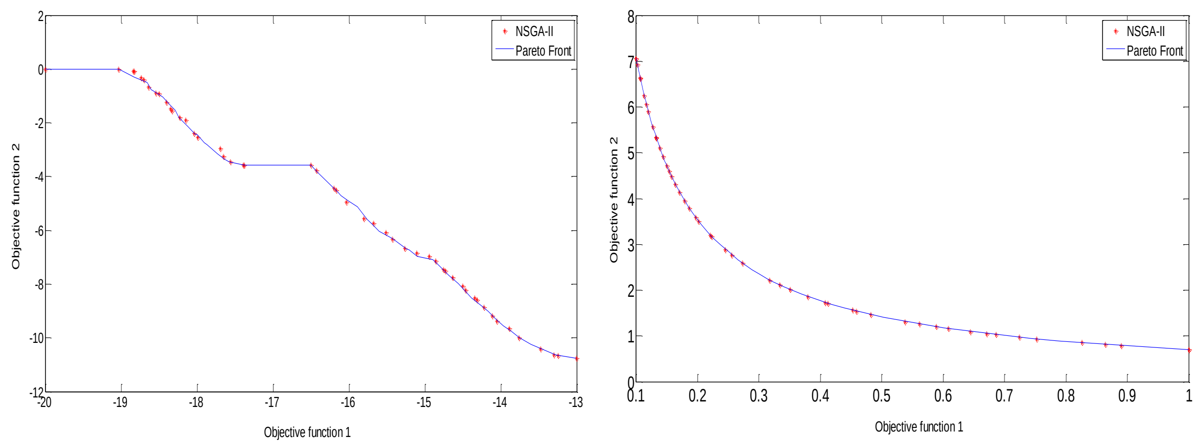

Figure 6. Kursawe (left) and Deb1 (right) test problems

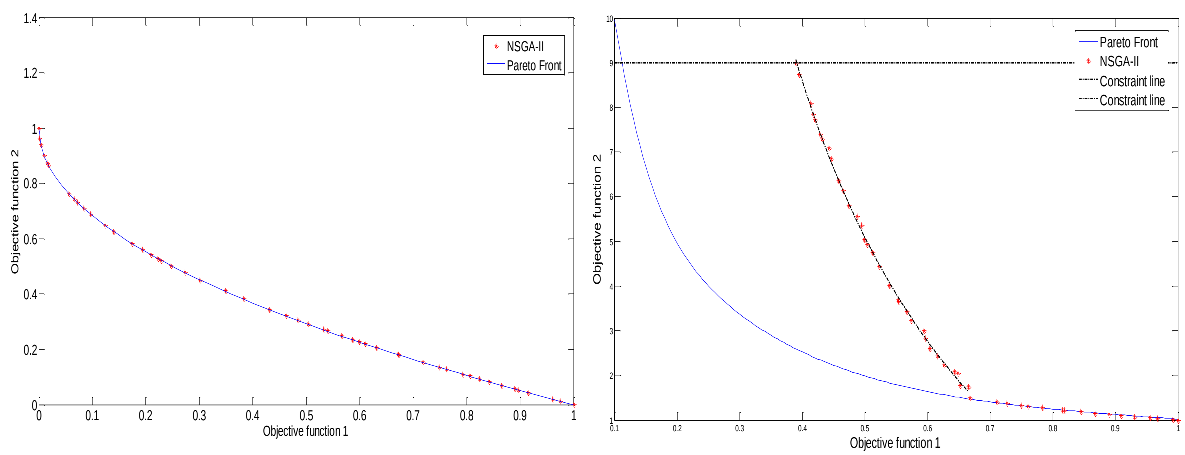

Figure 7. ZDT T1 (Left) and Constrained Deb2 (Right) test problems

Kursawe[14], Deb[13] and Zitzler, Deb and Thiele[12] test problems have 3,2 and 30 design variables respectively. A constrained Deb[2] function has 2 design variables and 2 constraint functions.

Fig. 6-7 demonstrates NSGA-II converged to a global Pareto front for both constrained and unconstrained problems. It was also observed from validation results of NSGA-II in Srinivas[11] Zitzler[12] and Deb[2] that the algorithm illustrated properties of a fast non-dominated sorting procedure and the Elitist strategy evoked better convergence of the global Pareto front. A comparison against other MOGA codes in the above literatures illustrated NSGA-II converged much better and obtained a more accurate global Pareto front.

IV. Results

The Multi objective Genetic algorithm optimization problem is formulated as follows:

$$\text{Objective function 1:} \quad min(C_L)$$
$$\text{Objective function 2:} \quad min\left(\frac{\partial C_L}{\partial h}\right)$$
$$\text{Subject to:} \quad C_L < 0$$
$$*C_M < 0.6$$
$$PARSEC\ bounds = [*\ Refer\ to\ Table\ 2.1]$$
$$\text{h/c} = [0.25: 0.05: 0.35]$$

*Note FIA[10] does not specify information regarding C_M. However a high C_M will destabilize the balance (in terms of cg location) and affect the overall performance. A maximum value of C_M corresponding to the selected airfoils is selected.

NSGA-II used a population of 50 points and evolved them for 500 generations, for a total of 25,000 function evaluations and converged to a global Pareto front for an estimated time of 3 hours, as shown in Fig 4.1. For a case of analysis, three optimum points were selected based on trade off and comparisons against the initial population. Fig. 9,10 and 11; illustrates a high down-force coefficient, minimum down-force gradient, and a best shaped airfoil respectively.

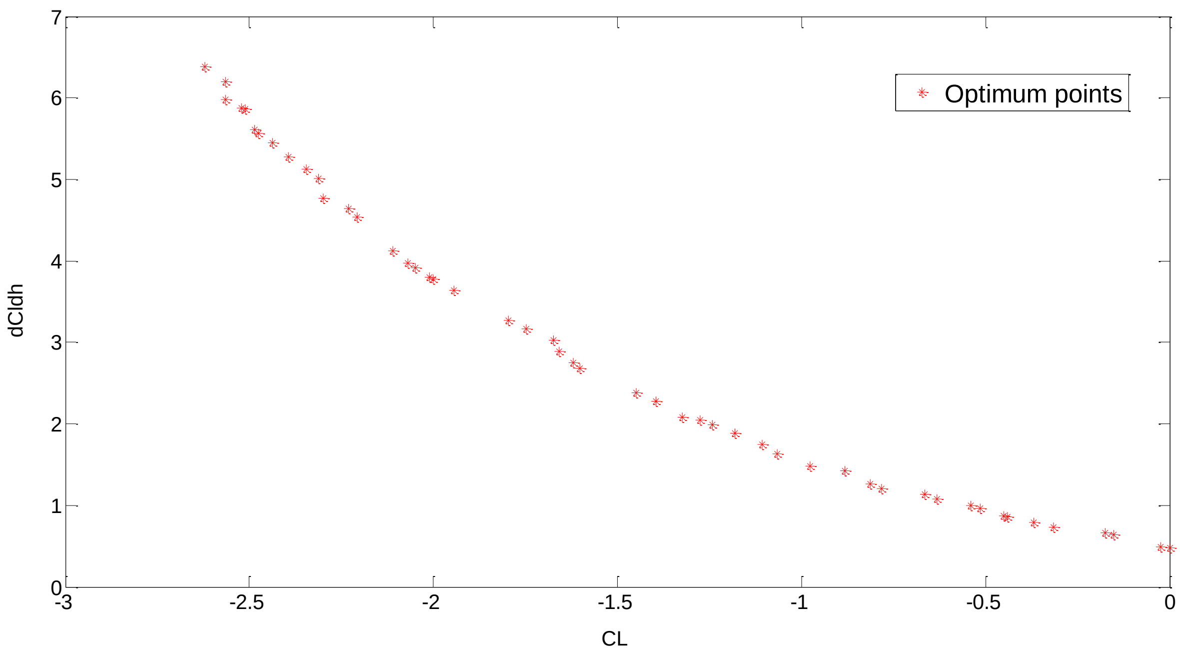

Figure 8. Global Pareto Front

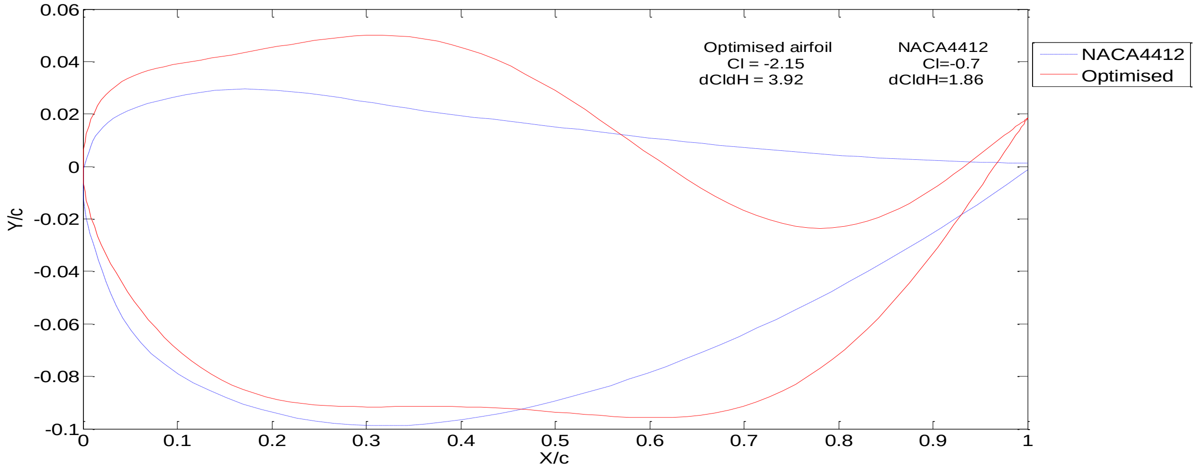

Figure 9. PARSEC 0.02126; 0.3026; 0.0917; -0.225; 0.313; -0.05 ; 1.0287; -0.3576 ; 0.234; -0.01877

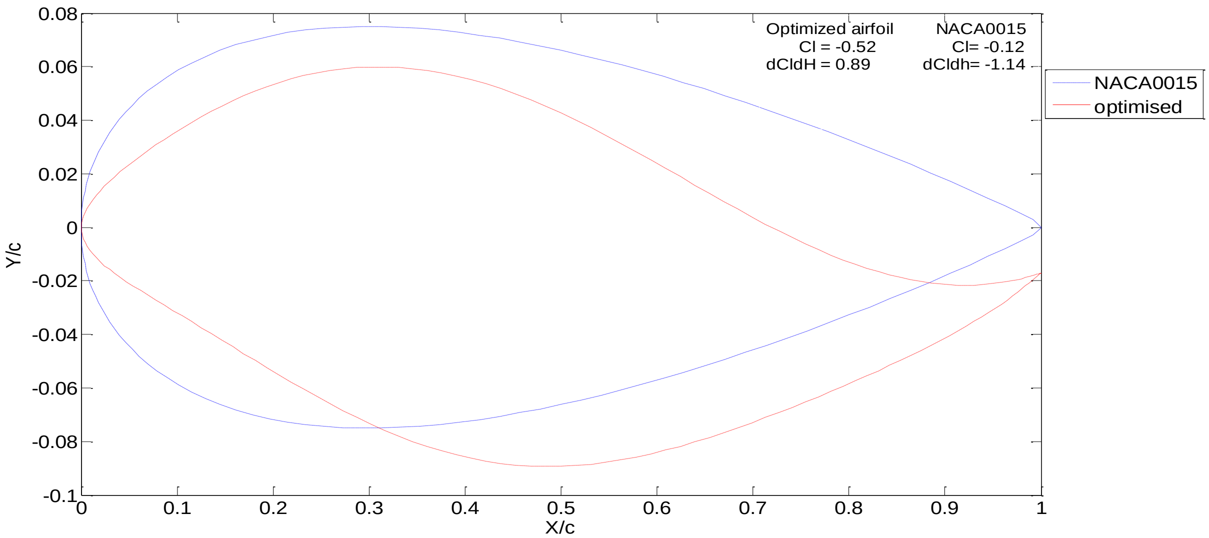

Figure 10. PARSEC 0.0041; 0.4869; 0.0893; -0.9064; 0.3100; -0.0599; 1.0742 ; 0.1894; -0.2096; 0.0171

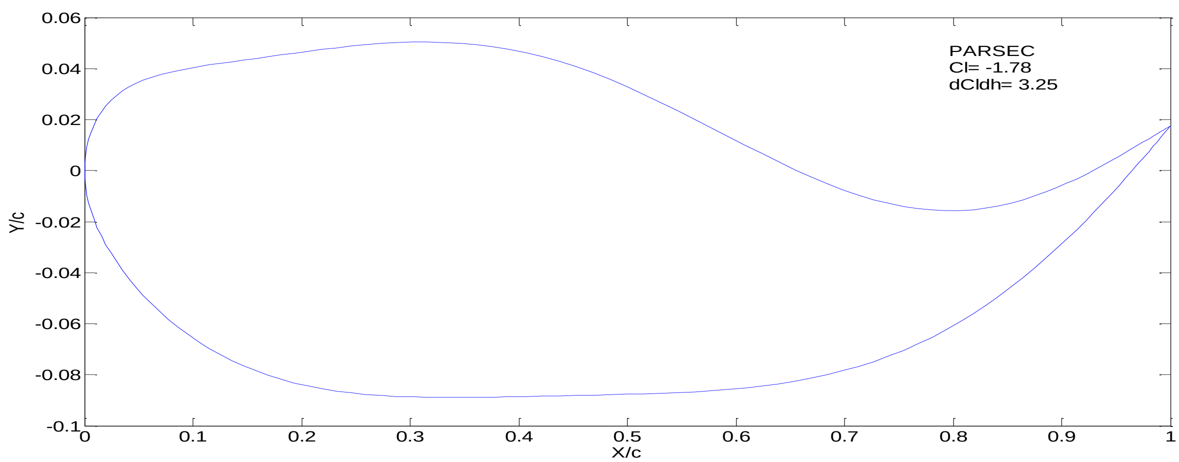

Figure 11. 0.020; 0.338; 0.089; -0.246; 0.314; -0.050; 0.858; 0.234; -0.356; -0.017

Two optimisation problems are presented. Maximising the down-force in Fig.9 is an important issue with regards to cornering speed. The idea was to maximise the down-force significantly above the initial set of airfoils. A conflicting problem is a penalty in stability. An increased down force resulted in an increased down force gradient. To investigate this problem, a Pareto front in Fig.8 was determined by a series of bounded set of airfoils. Three optimum points were considered as a trade off for the overall optimum airfoil. A selected optimized PARSEC airfoil illustrated a down-force coefficient of -2.15, almost double from the selected airfoil range. The optimized down-force gradient obtained in Fig.10 decreased approximately 50% lower without the expense of down-force. A third trade off consisted of a smoother streamline of the airfoil shape in Fig.11 that was observed more application to Formula One Application. The global Pareto front can extend its use further as a guideline of airfoil selection to target specific Formula One race tracks. The magnitude of down force is dependent on the types of corners offered. The Pareto front provides a wide variety of optimized airfoil selection.

V. Conclusion

An optimization procedure has been carried out using NSGA-II MO GA. A NSGA-II has been used to obtain the global Pareto and the performance has been shown in some sample routines from the literature and for a more challenging Formula One application. A conflict between down-force and down-force gradient transpired. A trade off was required on the global Pareto front which resulted in an intelligent selection of three optimized airfoils. The results showed a major increase of down-force compared to the initial population. The other trade off airfoil illustrated a major decrease in down-force gradient without the penalty of losing down-force.

This paper documented a quick, simple and reliable method of optimization for a Formula One Front wing application. The study forms a good basis for further optimization design in Formula One wing design. Drag is another important aspect that was ignored due to complexity of the algorithm. Drag minimization is a key design criterion in Formula One. Further research will investigate the viscous effects and add minimizing drag as the third objective function.

Acknowledgments

The research was supported by an RMIT Research Graduate Robert Carrese. A special thank to Robert for all his support.

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