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PARSEC PARAMETERIZATION METHODOLOGY FOR ENHANCING AIRFOILS GEOMETRY USING PSO ALGORITHM

Rafael Alves da S. Neto, sneto.eng@gmail.com

Luciano Gonçalves Noleto, lucianonoleto@gmail.com

Josiane do S. Aguiar de Souza, josiane@unb.br

Universidade de Brasília, Campus Gama

Área Especial, Projeção A, UnB - Setor Leste - Gama, Distrito Federal 72444-240

Antônio Cesar Pinho Brasil Jr.

brasiljr@unb.br

Universidade de Brasília, Campus Darcy Ribeiro

Campus Universitário Darcy Ribeiro, Brasília - DF, 70910-900

Abstract. *The electromechanical generating system is mainly based on the characteristics wherein the turbine has to "harvest" the energy of a working fluid. Thus, the engineering behind the blades, such as the geometry and construction, must be effectively consolidated to increase the overall turbine efficiency. This work aims to go further into the computational principles of modeling the turbine blades, precisely, the hydrokinetic turbine hydrofoil built by LEA (Engineering Laboratory and Environment - UNB). The study has a focus on designing and analyzing, through numerical studies of parameterization and optimization profiles, blades using computational tools such as MATLAB R2016b and XFOIL. In this case, the model study is part of the airfoil theory combined with the Particle Swarm Optimization technic (PSO), which are implemented to get a maximum utilization of the aerodynamic coefficient CL over CD of the blade. Furthermore, an optimal turbine blade geometry, set by PARSEC parameter, is found and compared with results obtained from the original hydrofoil, using the software of profile analysis XFOIL, to certify the mathematical method, proving its effectiveness to parameterize hydrodynamic profiles and optimize their geometries.*

Keywords: *Hydrokinetic Turbine. Airfoils. Parameterization and Optimization. Parsec. PSO.*

1 INTRODUCTION

The decentralized structure importance of the energy generation capacity ("smart grids") is due to the apparent economic infeasibility in installing electric power transmission lines for all types of consumers. For this reason, the study of alternative sources is a key point, for social reasons, human development and economic issues. Therefore, the use of hydrokinetic machines does not denote an innovative concept, but a review of existing models as an alternative for sustainable and reliable energy generation (Van Els et al, 2003).

The hydrokinetic turbines work with a water flow in a river or ocean. As watermills, these devices use hydrofoils as a way to "harvest" the energy of free streams of a fluid flow, using the difference in pressure gradient to generate a positive lift on its profile, so that generates torque, and therefore power (Grant, 2009).

In order to improve the overall efficiency of a turbine, the computational numerical data represents a faster and efficient way to get solutions, as it has the ability to meet various parameters from an old experimental database, enabling the scope of new optimized projects within a computer programming.

However, the description of a hydrofoil geometry is complex due to its parameters, like leading edge and trailing edge representation, which cannot be representated by a low geometrical derivative. For this reason, a great number of coordinates must be applied to the process in order to return a accurately geometry pattern in a computation environment.

Consequently, it is necessary to understand and develop a parameterization methodology of blade profiles in order to use fewer possible parameters to describe the given geometry in computational framework, which was explored in this work.

The algorithm generates many solutions, and in one of these solutions, the optimal setting should be included. Ahead, by an iterative method, the final result is found by the junction between parameterization, optimization and numerical analysis and simulations, to meet the need of a well-developed computation process, satisfaying topics like:

1. To generate continuous and closer to reality surfaces;
2. It has to be, in computational terms, faster with a certain accuracy and consistency throughout the body of the algorithm;
3. It needs to be able to represent a lot of airfoils with few parameters;
4. Finally, it must have a consistency in the profile creation process, as well as being able to change the geometry;

These objectives have been described by Kulsan and Bussoletti (2006), and item 3 relates the most important criteria in this paper.

2 PARAMETERIZATION METHOLOGY PARSEC/BSPLINE

Recently, there are many types of parameterization methodologies, mainly applied in aerodynamic optimization of aircraft wings.

Analytical functions are a method that is described in many of these studies, because they can represent airfoils by polynomial representations instead of using high amounts of coordinate points.

Theoretical modeling is done obeying the standards developed in literature and airfoil design about parameterization and optimization processes. In summary, through the airfoil database, the parameterization PARSEC methodology translates the Cartesian coordinates into 11 parameters (polar coordinates - Fig. 1), describing any airfoil with high accuracy. It was first studied by Sobiesky (1998) whose work used algebraic and analytical relations to generate realistic geometries based on airfoil families, such as NACA, GOE, Joukovsky.

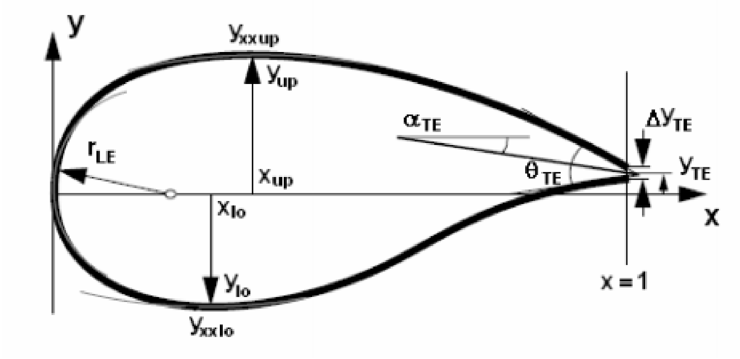

Figure 1: 11 Parsec parameters for an airfoil representation.
Adapted from Sobieczy (1998)

The 11 parameters are representations of physical characteristics of a given airfoil. Moreover, in order to build new profiles based on this specific representation, it would be necessary to have the description of basis functions for each one of the 11 parameters to recreate new 11 viable parameters. Therefore, the integration with a parameterization that does not involve physical quantities, such as Bspline, was adopted as the basis for the optimization process.

Bspline parameterization is an evolution of Bezier curves described by Consentino (1986). The contrary of Bezier that uses segments of "functions of Bezier" according to its degree, Bspline curve is defined as a linear combination of control points function and bases to assure that the curve can be represented in a simple degree polynomial representation and continuity. It was first studied by Shoenberg (1988).

These 11 parameters found by Parsec metholody are then stored for the new airfoils baseline generation by BSpline in parameterization process.

The method used to find the parameters, in this paper, is to use base functions created from the LEA turbine foil and solved by a linear system of Minimum Squares Error principle.

The representation of the specific turbine can be made following the expressions:

$$y_e(x_e) = \sum_{k=1}^{6} \alpha_{ek} \mathbf{x_e}^{k-\frac{1}{2}} \tag{1}$$

$$y_i(x_i) = \sum_{k=1}^{6} \alpha_{ik} \mathbf{x_i}^{k-\frac{1}{2}} \tag{2}$$

$$\alpha_{i1} = -\alpha_{e1} \tag{3}$$

The profiles characterized by PARSEC parameterization are defined by two polynomial functions and one boundary condition, as can be seen. The first two functions describes the airfoil boundaries, and the contour determines the leading edge condition. The representation is then used first to determine the base coefficients by the least-square method, each one minimized between the original cartesian coordinates represented by *x* and *y* variables.

The algorithm followed the method:

1. The derivative form of Eq. (1) is assumed to represent the miminium function for the upper camber solved by the Eq. (4):

$$y'_e max = 0 = \sum_{k=1}^{6} (k - \frac{1}{2})\alpha_{ek}\mathbf{x_{emax}}^{k-\frac{3}{2}} \tag{4}$$

2. The derivative form for the lower camber from Eq. (2) is written in Eq. (5). Moreover, both of these equations are used to state a linear system to solve the arfoil coefficients *'a'*, and then, the 11 Parsec parameters:

$$y'_i min = 0 = \sum_{k=1}^{6} (k - \frac{1}{2})\alpha_{ik}\mathbf{x_{imin}}^{k-\frac{3}{2}} \tag{5}$$

3. Set the 11 parameters to the Bspline function base in order to randomize new parameters.
4. Each new parameter represents one different airfoil that needs to be analized by a CFD software. For this case, XFOIL software developed by Drela (1989), to find the best one.
5. The optimization algorithm is the one to call the Bspline parameterization to create new airfoils. Then, they go through a iteration process that penalize bad designs and promote the best ones.
6. The process ends when it can no longer find the best geometry, or when the maximum iteration process is reached.

It is important to ilustrate that the success of any parameterization method is related to how accurate the calculation can solve the sensitivity derivatives (Li and Padula, 2004). As well, in oder to apply even more realibility, smoothing process in the basis function is used after each iterations.

3 PSO OPTIMIZATION

Particle Swarm Optimization (PSO) is a optimization process based on stochastic population technique and it shares many similarities with Genetic Algorithms (GA) although it has no evolution process such as crossover and mutation. It was developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the flock of birds behavior or school of fish (Xiaohui Hu, 2006).

Basically, the system is initialized with a population of possible solutions, and it demands in that universe, the best one, making improvements in each generation. However, contrary to the GAs, PSO is not an algorithm based on the evolution operators, as already said. Potential solutions, also called particles, move within the sample space following ones closer to others solution particles. Apart from that, they also have internal memory, a fundamental part in each iterations.

PSO starts with a group of random particles, in this case, airfoils. Its operation is based on "the learning scenario" and uses it to solve the optimization problem. In each space there are many "particles" that have fitness values, which are evaluated by a fitness function to be optimized (Xiaohui Hu, 2006). The particles also have velocities which help ”the movement” in the space following the current optimum particles. It can be associate with an example given by Xiaohui (2006) in IEEE Congress on evolutionary Computation: a group of ducks (particles) in a random search, looking for food (objective) in a lake (given space). There is only one place in that given space with food, but the ducks do not know exactly where, even though they feel how close they are in each iteration. Furthermore, the group of ducks follows that one duck which is closer to the main goal.

At the begining, the optimum solution is the airfoil which was set by the user to be optimized. Then, this airfoil is parameterized in random solutions and analyzed one by one to set the second best solution to be followed, which takes place to the first one. The algorithm goes on until it finds the objective value also set by the user.

There are a few variables that need to be used in order to structure the algorithm, mainly described in Xiaohui Hu (2006) tutorial. One of the most important variable is the particle velocity, which is described by the Eq. (6), because it relates how fast and how accurate is the result to be found.

$$v() = v() * w + c1 * rand() * [pbest() - present()] + c2 * rand() * [gbest() - present()] \quad (6)$$

One of the characteristic of PSO is that it does not eliminate bad designs like most of optimization processes. On the other hand, PSO penalizes those which goes far from the set constrains.

4 RESULTS AND ANALYSIS

The algorithm in Matlab was established in order to follow certain iteration cycles, which can be inferred from the sequence, parameterization, optimization and the results analysing.

For the code initialization, the airfoil profile, which will be optimized has to be described in a file ’.dat’ format with the Cartesian Coordinates. Then, in the process, the polynomial variables are solved to acquire the 11 parameters required to enter the next stage of the optimization sequence. Afterwards, the algorithm reverses by the transformation function the parameters in new Cartesian coordinates.

The original blade was built by a particular mechanical design, which means, it was made specifically for the required characteristics of an internal project without following any of determined airfoil families.

The Panel Method used in Xfoil software, have well-defined inputs that dictate the project execution. One of those entries is based on polar coordinates of the airfoil to be studied. In order to do so, the Cartesian coordinates were found by using the *Shape Design tool* of CATIA V5 software platform as can be seen on Fig. (2).

After the Cartesian coordinates is obtained, the process starts to get the parameter bases and to analyse them in each iteration to determine how the aerodynamic airfoil meets certain requirement. Xfoil allows to vary different parameters according to the operator’s will on a particular aspect of evaluation. This means that can be set in the Matlab code the evaluation principle, like attack angle, lift coefficient, drag coefficient and so on.

It can be noticed from Fig. (4), the boundary layer shift when it reaches an angle of attack of 16° represented by the sudden decay of the supportative curve and the boundary layer (yellow)

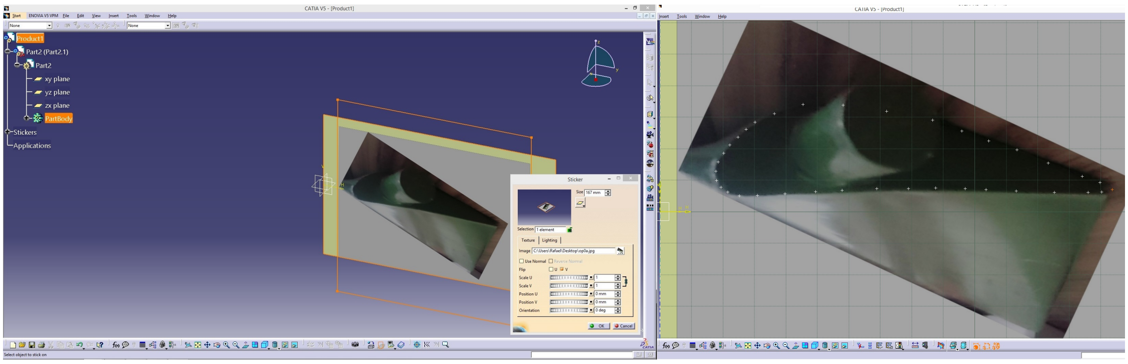

Figure 2: Original airfoil (LEA)translated to Cartesian coordinates using the software CATIA V5.

in Fig. (3). This separation, called by the term stall, is clearly seen in solid bodies through a fluid flow, mainly in high speeds and/or low viscosity fluid, which generally leads to a higher Reynolds number. The *stall* leads to a poor airfoil configuration but it can be smoothed by the construction materials (like wall friction) due to the viscosity effect, but mostly delayed by adverse pressure gradient.

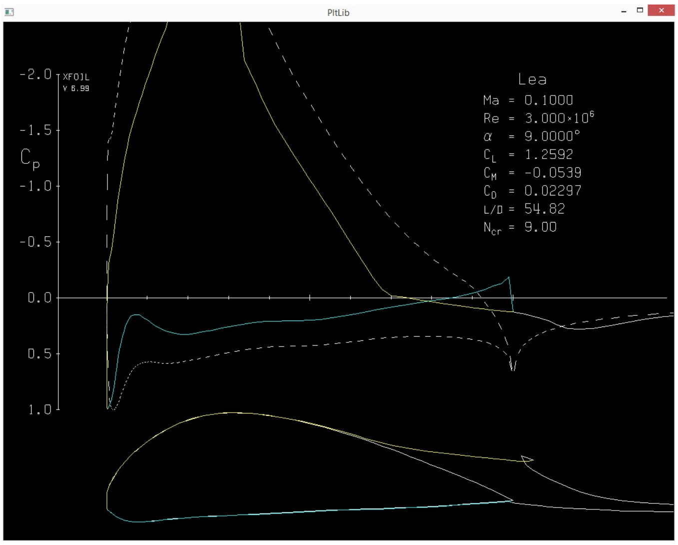

Figure 3: Panel method with boundary layer analysis set by Xfoil software.

Relating the Reynolds number, for example, in a river flow, the particles in the fluid, hitting the hydrofoil walls in question, has lower speeds than the rest of fluid by the effect of viscosity. Therefore, the energy and momentum of the particles do not resist the adverse pressure gradient due to an increased angle of attack. Then, the particles near the surface are forced to follow in the reverse direction to the fluid due to low local pressure, causing the boundary layer loss on the hydrofoil wall, creating a positive pressure coefficient at that point, causing lift loss and turbulence.

The Xfoil software returns, in addition to the polar profile, the performance characteristic parameters in arrays. The algorithm scans the matrix and determines the point at which the relationship Cl over CD is the best among the specified range of verification, which varies with the airfoil angle of attack of 0 to $25°$. For the original turbine, the optimum point is with an alpha (angle of attack) of $10.5°$ representing a 1.6 lift coefficient, as can be seen in Fig. (4).

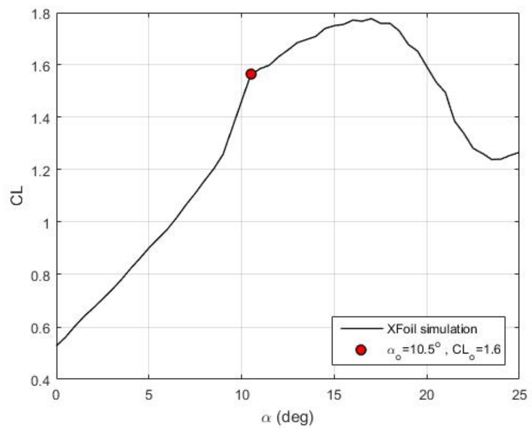

Figure 4: Original airfoil representation for Cl and the range $0°$ to $25°$ of attack angle, as well as the optimum point for Cl/CD.

Figure (5) represents the relation between the PARSEC parameterization and the original airfoil. The representation by the eleven parameters of that method is highly effective to airfoils from the NACA family, with differences between the geometries of only 3 basis functions. However, the airfoil study has a very peculiar profile, approaching the Goettigen German family, with a very sharp thickness near the aerodynamic center of the blade, which makes the exact construction of the parameterization by this method, difficult. Therefore, it can be noticed a disturb in the profile of the leading edge, but despite some variations, tolerance thickness error in airfoil in a wind tunnel reaches 0.1% is satisfied (Kulfan, 2006). This oscillating feature is common in minimizing functions by least-squares.

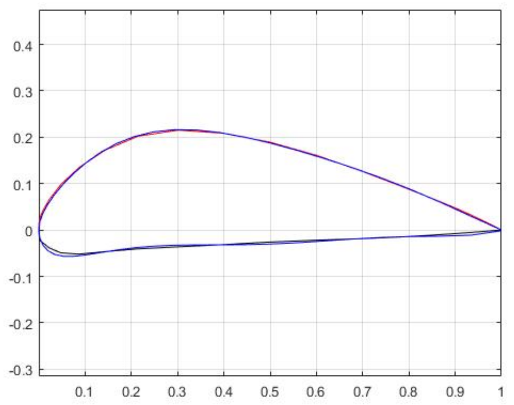

Figure 5: Geometric representation of original (red) and parameterized hydrofoil (blue).

Finally, the first step, the four main representations of the original airfoil characteristics can be seen in Fig. (6).

4.1 Optimization results

The iterative method returns a sample map which contains the convergence numbers of the optimization method. The objective function is peculiar to the purpose of the algorithm, therefore varies according to the operator desire. In this study, the objective function was defined to

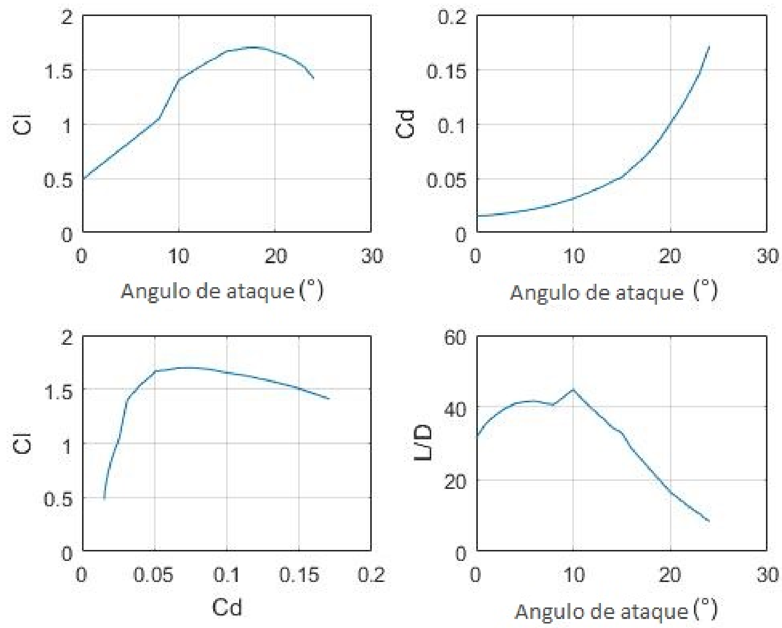

Figure 6: The four main airfoil characteristics from the original hydrofoil given a range of 25 points of AoA.

maximize the ratio CL / CD, as discussed in the optimization session. The optimization ends after 30 iterations without achieving any improvement in the relationship. To optimize the airfoil in question, 157 iterations, as shown in Fig. (7), with a sample space of 25 points were necessary, which means 25 airfoils at each iteration. Thus, 4710 functions are evaluated what denote 9420 different airfoils forms evaluated by the algorithm as the Xfoil calls them 2 times for better accuracy.

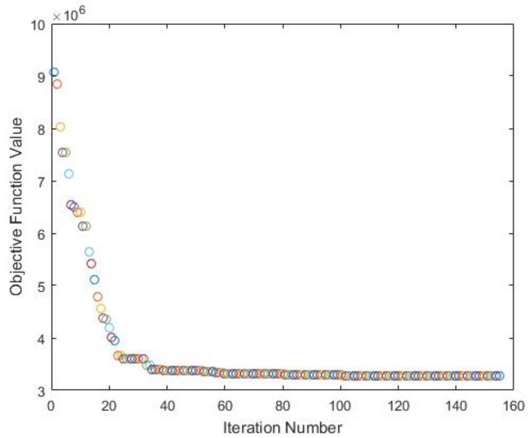

Figure 7: Sample map of iteration numbers.

Following the optimization sequence, the iterative process is represented in Fig. (8). Each image represents a different airfoil model. Basically, the base profile built by PARSEC parameter is modified in its parameters to generate new profiles. These profiles, then, pass through the optimization process, and the basis functions that describe each is configured to converge into the most appropriate purpose airfoil. Note that there is a certain regularity in the construction of profiles after the $40°$ iteration, slightly varying the profile.

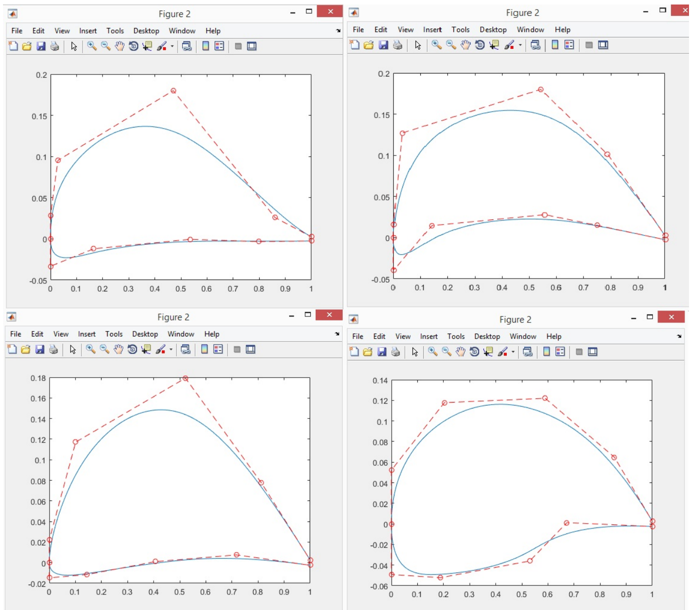

Figure 8: Iteration process of randomizing new airfoils from a given original airfoil (*seed function*).

If the operator, set the optimization for the drag coefficient, the iterations converge to a minimum thickness, as can be seen from Fig. (9). In this study, the algorithm and generating airfoils trying to find a balance between CD and CL.

The first series of tests returned the airfoil of Fig. (9). It is noted in the figure that the results were satisfactory for both purpose specified and the optimum range. Compared with the original airfoil, there was a gain of more than 80 units in the ratio CL / CD, reaching 126 u. against 43 u. from the G2 turbine profile. However, the optimum angle of attack for this remained at $10.5°$, while the optimized profile decreased to $5°$. It can be seen from Tab. (1), both results, original profile and optimized one.

Table 1: Cl/Cd comparison between original and optimized airfoil in each optimum angle.

Angle of Attack (°)	**original Airfoil** (u)	**Optimized Airfoil** (u)
10.5	*43*	*77*
5	*41*	*126*

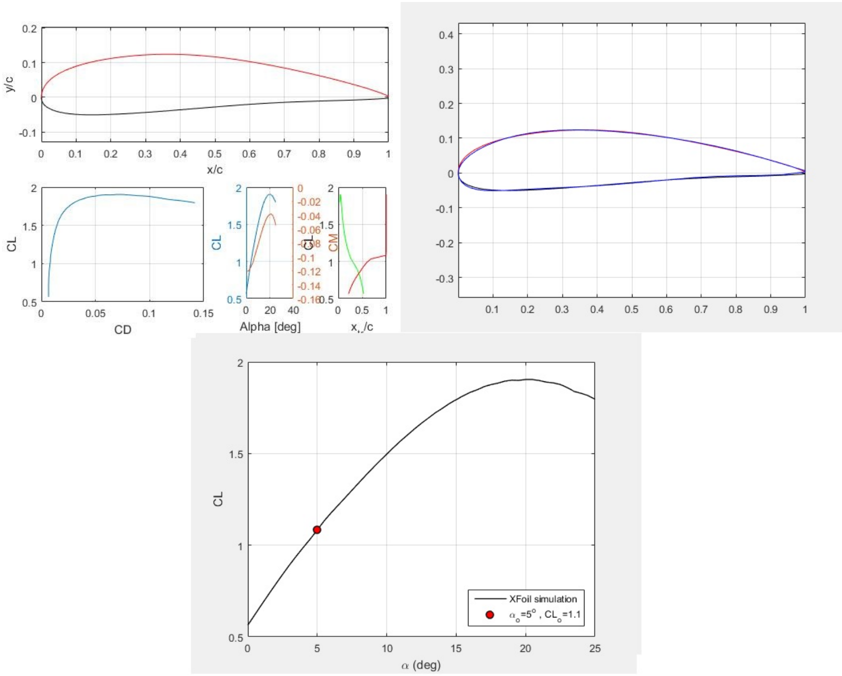

Figure 9: First results from the optimization process without thickness constrains and CD minimization objective.

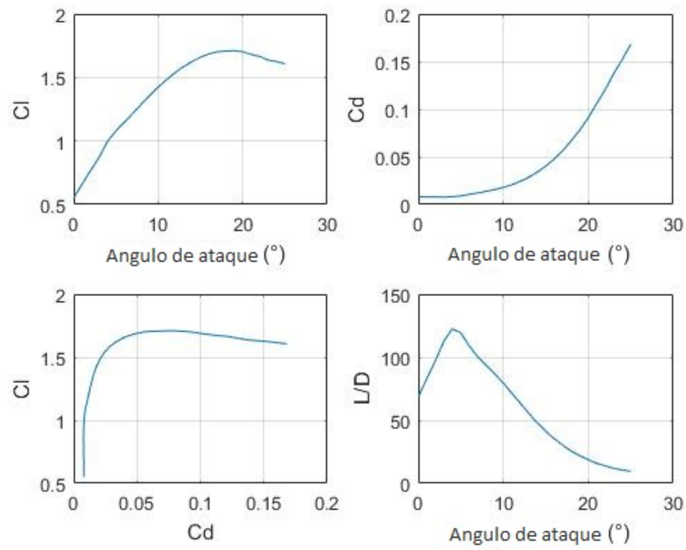

Figure 10: The four main airfoil characteristics from the first optimizated hydrofoil in a range of 25 points of AoA.

By contrast, the drag coefficient had a growth rate below the current profile, which contributes to the increase of the ratio to be optimized. This is due to the fact that the profile has considerably decreased the local thickness, and have been softened both the leading edge and the trail, what gives greater smoothness to the flow and optimizes the point of *stall*, main issue in generating adverse support forces. However, with low thickness profiles, beyond the construction limitation, it has high beneficial results related to lift properties and consequently greater blade rotation. Therefore, increasing rotation, leads to increase tangential velocities and also to increase shear forces, providing greater turbulence.

On the first test, we can see from the results that the algorithm tends to optimize airfoil decreasing the thickness of its profile. The difference is quite pronounced if no set boundary conditions in accordance with the original profile is provided (22 u - Fig. 5 versus 15 u thick - Fig. 11). This is due to the fact that one of the main evaluation parameters of the algorithm is the drag coefficient, as well as already shown, the objective functions that set the course of optimization. These objective functions dictate the penalties to be imposed on the main functions of optimization, and such, the more "thin" the profile is, the greater is the resistance to the displacement of the boundary layer, and therefore less drag.

Figure (11) is the second test, considering the thickness limits of the original airfoil. Note that the thickness of the trailing edge was quite changed, giving a low drag for small angles of attack. Indeed, while increasing the same angle, the drag grows as an exponential factor.

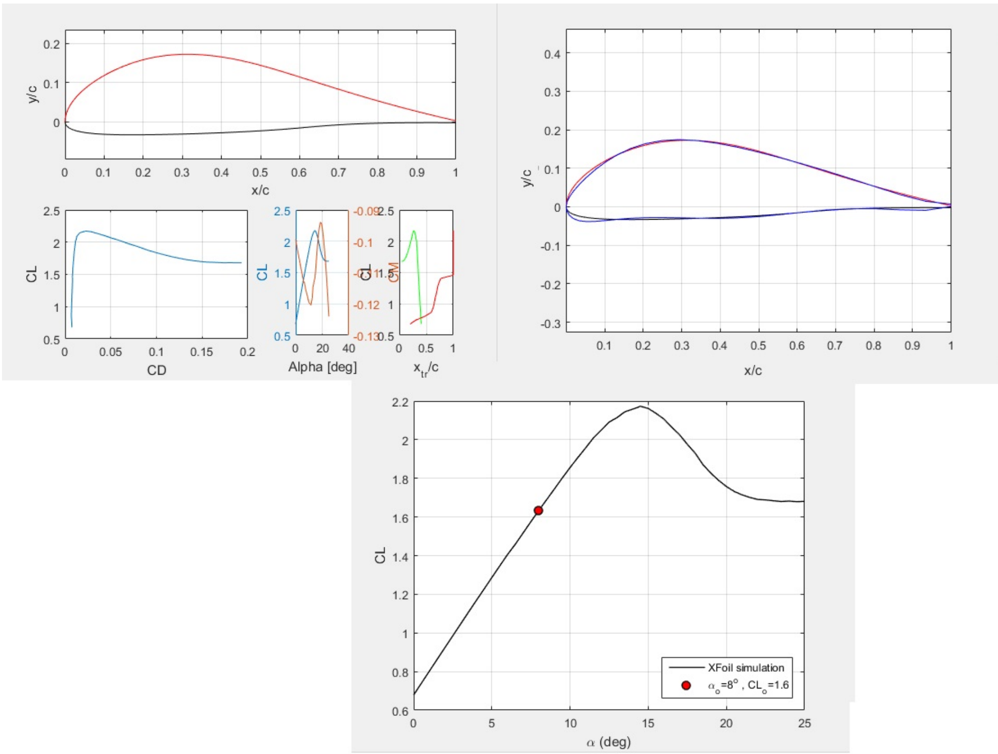

Figure 11: Second results from the optimization process with thickness constrains and Cl/CD maximition objective.

The results from the main characteristics at the first optimized hydrofoil in Fig. (10) compared to Fig. (12) shows that the AoA range was optimized according to the operator (0° to 10°). Even though, the first hydrofoil could stabilize the lift coefficient, the relation L/D was stabilized by the second one. It can be seen in the fourth graphic.

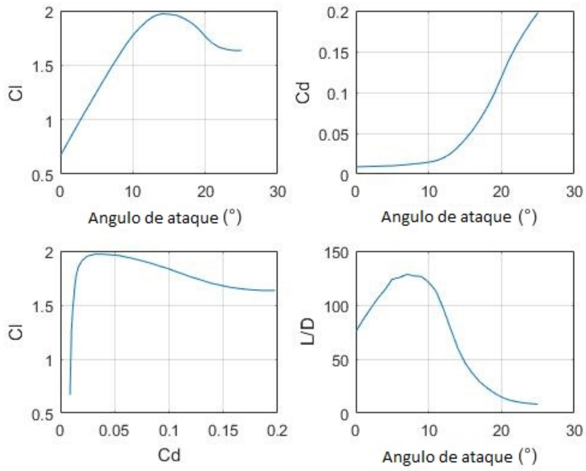

Figure 12: The four main airfoil characteristics from the second optimizated hydrofoil in a range of 25 points of AoA.

Figure (12) translates the main characteristics of the second airfoil optimized. In the algorithm, it can establish which parameters and which optimization range the airfoil could be subjected. This study, it was defined the angle $(0°, 10°)$, which means, the iterations will focus on the parameters of that given optimization range. It is observed that after a limit of $10°$ parameters begin to decrease, particularly the L/D ratio, which shows the algorithm efficiency and fidelity to track the operator sets up. Note that the drag coefficient increases exponentially after the range, confirming the optimization of the statement within the set values.

The generation of these optimal parameters has been expended 4 hours and 13 minutes. This value changes depending on the complexity of the airfoil and the objective function. As stated, the main goal of this optimization was the maximization of the ratio CL/CD by the PSO optimization algorithm, so the whole amostral space was set to pursue the best value for the specified aerodynamic property.

The entire process took place in an operational system governed by Windows 8 platform, with Matlab 2015 and Xfoil 6.9 software. The hardware is governed by an Intel i7 processor, 4 GB of RAM.

```
>> Main
Rodando Xfoil. Por favor, aguarde...
Analise Xfoil terminado
      Parametros Parsec:0.035315     0.29312     0.17412     -2.3054     0.38061    -0.030269     0.55926   0.0036164   0.0062773     0.14816     0.28609

      alpha opt.:8
      CL    opt.:1.6335
      CD    opt.:0.00875
```

Figure 13: Parsec parameters and optimum point configuration for the last optimized airfoil.

5 CONCLUSION

The use of computational process, as an important tool in understanding the physical phenomena, is something already proven. Furthermore, it is concluded that the optimization methodology and airfoil analysis used in this paper were satisfactory for the quality of the results generated, such as by the reasonable computational burden. The algorithm proved to be powerful in certifying development issues and aerodynamic designs evaluation.

The code deployment, as well as the interaction between its different factors has its difficulties, because dealing with computer programming routines with many iterations require caution, especially because of error propagation. However, it was found that a division of MATLAB functions could minimize this problem because each one validated its goals before solving the problem.

Regarding the parameterization, the PARSEC polynomials proved to be efficient in the airfoil description as a parameter generator, though, reducing them, some errors of the first derivative function can still be seen. The 11 parameters that describe the airfoil cover a wide range of families, although in some cases, the error is accentuated more than others. Moreover, the representation has a simple formula to be implemented which makes the method one way of testing simple optimization problems.

The Bspline parameterization is concise for cases with specific solutions, because it uses control points to represent the geometry curves. Furthermore, they can be randomized from Parsec basis in order to generate other airfoils with a structural basis similar to the original one. The fact of using these two parameterizations was exactly that, because the airfoils generation capacity by an iterative process is more flexible with Bspline. It is due to the geometry, which is not defined with specific physical characteristics, facilitating the random process of creating new shape designs in the optimization process. In addition, the operator can have greater control and flexibility on the airfoil surface by modifying the polynomial degree, and the number of control points, non-existent in Parsec parameterization.

The PARSEC and BSPLINE integration helped in the optimization process because the PSO algorithm uses randomized airfoil database to describe the search process for the optimal airfoil. However, it was found that there is a problem in the iterative process, because the bad airfoil designs were not discarded, as in the genetic algorithms. They have been stored in the internal memory, and sometimes the algorithm brought them up again to be tested if there were not a significant ”punishment” quad on them. For this reason, the first iterations were too slow to be completed. On the other hand, this problem can be partially solved by the use of a geometric viability control of the airfoils, avoiding unfeasible profiles, and reducing the computational waste.

Finally, the results were satisfactory for the purpose of this work. For the original airfoil, there was a gain of more than 80 units in the ratio Cl / Cd, reaching 126 u. versus 43 u. of the G2 turbine profile. Besides that, the lift coefficient remained relatively constant 1.56 u to 1.63 u. Moreover, the optimum angle of attack decreased from 10.5° to 8°, causing constructive limitations, but is consistent with the range set by the operator used for the optimization, from 0° to 10°.

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