Avoid aeroelasticity instabilities with a morphing airfoil using neural networks

(Bibliography report)

Raul Carreira Rufato* and Dr Joseph Morlier†
*Institut Supérieur de l'Aéronautique et de l'Espace (ISAE-SUPAERO), Université de Toulouse, 31055 Toulouse, FRANCE
Email: raul.carreira-rufato@student.isae-supaero.fr
†Institut Supérieur de l'Aéronautique et de l'Espace (ISAE-SUPAERO), Université de Toulouse, 31055 Toulouse, FRANCE
Email: joseph.morlier@isae-supaero.fr

***Abstract*—Avoiding an aircraft instability condition is extremely important, especially for flight control. Morphing airfoils can be used to control an aircraft in aeroelastic instability situations. This work proposes the determination of a morphing airfoil, using a machine learning approach, for a given unstable condition. Instead of using full coordinates, Bezier – PARSEC 3434 parameters have been used to describe the airfoil. Some of these parameters have been determined using a Genetic Algorithm. In the second stage, airfoil's Cg position, cl, cd and cm distributions for some angles of attack will be input into a neural net for learning and then estimating the corresponding BP3434 parameters. In sequence, the neural network will be coupled to the 2D aero model of a wing.**

I. Context

Historically, the study of airfoils has always been extremely important in the aeronautical industry, since they can be considered as the heart of the airplane [8]. Airfoils are also extremely important in describing the aeroelastic characteristics of a wing, so studying and improving its performance is highly essential. In this context, morphing airfoils are being studied, due to their ability to adapt to a given flight requirement, as this technology is aimed at very efficient aerodynamic and structural designs during flight, contributing to the high performance of aircraft [10]. The impact of this new technology, as well as simple modelling of this type of airfoil were better described in [3]. They are similar to the birds' ability to adapt their wings to certain flight conditions improving their performance.

In an aircraft, several situations that occur during flight can alter the global center of gravity and even that of the wing, such as jettisoning and fuel consumption, which can instantly bring the aircraft into an unstable condition. Therefore, using airfoils of variable geometry, allows the optimization of their shape, hence returning to a stable position. Due to the high non-linearity of this process, it is interesting to use artificial neural networks which are viable computational models aimed at a wide variety of problems, including optimization, nonlinear system modelling and control [5], and seek to represent the way the human brain works, being provided with neurons and connections between them. This modelling is one of the most modern ways to optimize highly complex systems and obtain acceptable results. This work links the study of the aeroelastic characteristics of morphing airfoils with the neural network tool.

II. Problem statement

Despite being a simplistic model, with a reduced number of degrees of freedom and in 2D, a few problems can occur, as in [6]:

- Construction of the database: for the construction of the database there is the need to carry out an optimization by differential evolution for each airfoil.
- To guarantee the training of a neural network with high accuracy and low loss function, a high number of airfoils and their respective parameterization is necessary, which further increases the time of the process.
- Difficulty in coupling the neural network model with the aeroelastic model.

Despite the problems that can occur, this research aims to develop a simplified model, although being very representative for this case study.

III. State of Art

Determining an optimal geometry for the morphing airfoil consists of a highly complex optimization problem because, in many cases, known airfoils are describe by a vector of 50–80 length, as listed in the UIUC Airfoil Coordinates Database [1]. However, using a form of parameterization through Bezier-Parsec curves as described in [9], it is possible to describe the geometric characteristics of an airfoil through a reduced number of parameters. Bezier's camber-thickness formulation is more directly related to flow than upper curve-lower curve formulation for PARSEC, while PARSEC parameters are more aerodynamically oriented than Bezier parameters. The BP parameterization uses the PARSEC variables as parameters, which in turn define four separate Bezier curves. These curves describe the leading and trailing portions of the camber line, and the leading and trailing portion of the thickness distributions [4].

The Bezier-Parsec parameterization can be seen in Fig. 1. Using the BP3434 parameterization it is possible to train a neural network as in [6], for a desired input vector. In this work, we chose to use the same idea to train a neural network using the Keras package in Python. Additionally, the

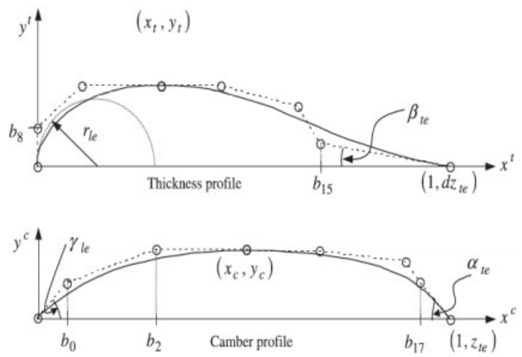

Fig. 1. BP 3434 airfoil geometry and Bezier control points defined by ten aerodynamic and five Bezier parameters [9]

coupling will be made with an aeroelastic simulation in which an airfoil will have undergone a sudden change in its Cg, taking it to an unstable condition. For the modeling of this airborne condition, a model like the one in [7] will be made. The neural network will then be able to determine a new airfoil (through BP3434 curves) to return the Cg to a stable condition, maintaining the same aerodynamic characteristics as the current profile.

To conclude, the construction of the database to train the neural network will be done using the Matlab software and the Xfoil code. Then the neural network and the aeroelastic code will be coupled in Python language.

IV. First results and future work

The research development started by building the database, which is important for training the neural network. First, the x and y coordinates were determined for the airfoil points of the NACA 4 family, varying: maximum thickness, maximum camber and location of maximum camber. Next, the 15 parameters were determined to describe the Bezier-Parsec 3434 curves, in which 7 of them were easily determined and the rest underwent optimization, using the differential evolution (DE) algorithm of Rainer Storn [2]. Finally, using the relationships between cramp curves and profile thickness, it was possible to determine the control points of the airfoil and then its estimated curve. The results of this approach can be seen in Fig. 2, for the NACA 2412 airfoil.

It is possible to see through Fig. 2 that the curve adjustment was well done given the amount of points that describes the airfoil. In Fig. 3, you can see the control points to describe the profile thickness and camber curves, determined by the Bezier-Parsec parameters.

Finally, for future work it is intended to complete the construction of the correct database to train the neural network that will be used, as well as define the parameters for the neural network, such as layer number and activation functions. In sequence, connect the trained neural network to the aeroelastic model that will be developed to predict the occurrence of instabilities mirrored in [7]. The final model will be able to

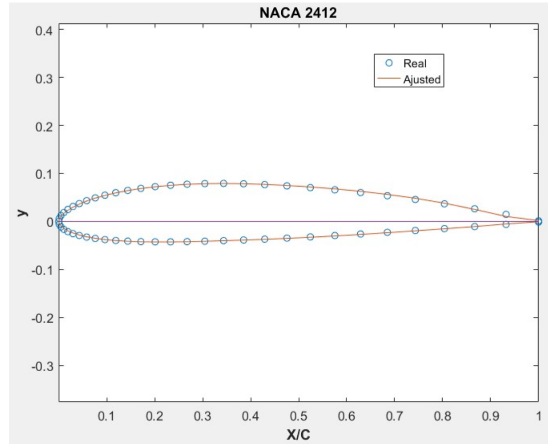

Fig. 2. BP 3434 parametrization: control points. Font: Author

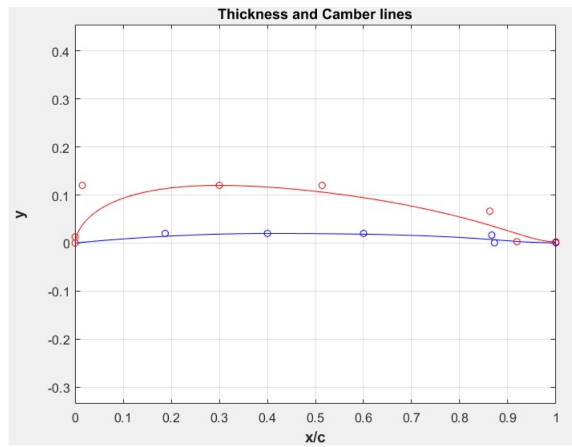

Fig. 3. BP 3434 airfoil geometry aproximation using Bezier-Parsec 3434 parameters. Font: Author

prevent instability by changing the geometry of the airfoil given the desired characteristics.

References

[1] http://www.ae.illinois.edu/m-selig/ads/coord_database.html. [Online; accessed on 20 May 2020].

[2] http://www.icsi.berkeley.edu/~storn/code.html. [Online; accessed on 01 May 2020].

[3] Jason Bowman, Major Brian Sanders, and Dr. Terrence Weisshaar. Evaluating the impact of morphing technologies on aircraft performance. April 2002.

[4] R.W. Derksen and Tim Rogalsky. Bezier-parsec: An optimized aerofoil parameterization for design. 41:923–930, 2010.

[5] Mohamad H. Hassoun. Fundamentals of artificial neural networks. MIT press Cambridge, Massachusetts, London 1995.

[6] Athar Kharal and Ayman Saleem. Neural networks based airfoil generation for a given cp using bezier–parsec parameterization. 23:330–344, 2012.

[7] V. T. Nagaraj and D. J. Johns. Flutter analysis of a wing with concentrated inertias by a direct matrix method. 1975.

[8] D.P. Raymer. Aircraft design: A conceptual approach. 2006.

[9] Nilesh P. Salunke, Juned Ahamad R. A., and S.A. Channiwala. Airfoil parameterization techniques: A review. *American Journal of Mechanical Engineering*, 2:99–102, no. 4 (2014).

[10] N. Tsushima, K. Soneda, T. Yokozeki, T. Imamura, H. Arizono, and W. Su. Structural and aerodynamic models for aeroelastic analysis of corrugated morphing wings. Jan 2020.