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ANALYSIS OF MLP ARTIFICIAL NEURAL NETWORK ARCHITECTURE FOR E423 AIRFOIL

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Abstract. *This work analyzes if a Artificial Neural Network with multilayer perceptron architecture is able to develop the Lift coefficient X α curve, without the need for numerous experimental tests. The airfoil used for the architecture analysis was the Eppler 423. The coefficients of lift (C1), coefficients of drag (Cd), different angles of attack (α) and different Reynolds numbers (Re) of this airfoil were used. For the network architecture two input data were used, and the output is the C_l. A total of 1000 training epochs were used, which means that 1000 complete presentations of the training set were made during the learning process, this number of times acts to the synaptic weights and the bias levels stabilize to obtain the Lower RMS. The cross-validation process is used in the network because it acts as an aid criterion to evaluate the robustness (data repeatability). The main analysis of the network is given by the robustness, which is found by graphically comparing the dispersion between the RMS test and RMS training. The results obtained, allows us to reach the conclusion that there is a good repeatability and the network is satisfactory, which was obtained a graph behavior quite satisfactory for some Reynolds numbers.*

Keywords: *Eppler 423, airfoil, Artificial Neural Networks, RMS*

1. INTRODUCTION

One of the greatest challenges in creating an airfoil is obtain the aerodynamic coefficients (lift, drag and moment) from the angles of attack. In this work we will consider the lift coefficient, the angle of attack and some variations in the Reynolds number.

The lift force is the force responsible for sustaining the plane in the air, so the higher the coefficient becomes more efficient is the airfoil for the flight. Since the drag force represents the friction forces generated by the airfoil, a low drag coefficient is ideal for a better efficiency.

To elaborate an airfoil is necessary obtain these coefficients by a function containing the angle of attack and the Reynolds number, which means that a change in the angles of attack generates a change in the other coefficients, the same thing happens if the drag coefficient is changed, the others change as well. There are other relevant coefficients for an airfoil, however these will not be approached in this work.

An Artificial Neural Network (ANN) can be classified as a type of processor, that is formed by other small units with capacity to store experimental data and through a programming made in that processor, bring results through this analysis. This analysis can be called learning, because the process of ANN development was based on the human brain, which has a process of absorbing knowledge as a form of learning and a stage where the connections between neurons occur to obtain a result (Haykin, 2001).

The use of the artificial neural network in this work was chosen because of the capacity of learning by items that it possesses and by the generalization capacity of information. The ANN used in this work will receive input and output data to make its learning, which means that it has withdrawn its main characteristics from the results analyzed (Braga *et al*., 2000, Haykin 2001, Kovacs, 2006).

The purpose of this work is to use the ANNs to analyze if it is possible to determine the curves of the lift coefficient X angle of attack for several Reynolds number of airfoil Eppler 423 and to observe if the network has generalization capacity.

2. METHODOLOGY

For the development of the analysis from the neural network, it was necessary to develop some steps, such as obtaining the data (from the airfoil to be analyzed), the data processing and finally the construction and training of the network until the selection of the best architecture to be used. The steps are shown in Fig. 1.

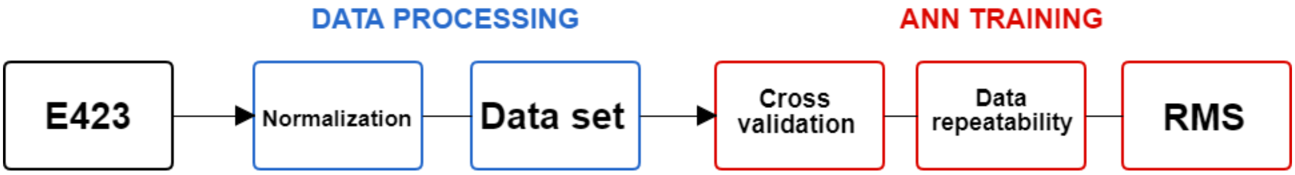

Figure 1. Flowchart of applied methodology

2.1 E423 airfoil

An airfoil is a projected surface with the purpose of obtaining an aerodynamic reaction from the flow of the fluid around it (Rodrigues, 2011). The aerodynamic airfoil used in the analysis was the Eppler 423, which has its geometry shown in Fig. 2, obtained in UIUC Airfoil Coordinates Database (2017).

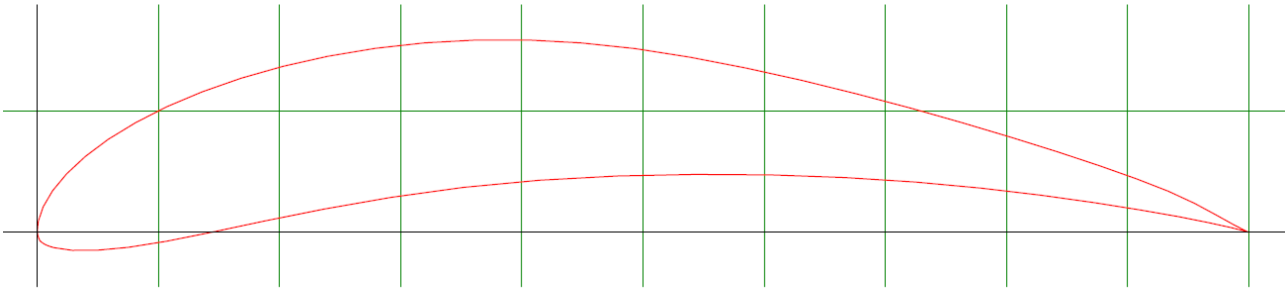

Figure 2. Eppler 423

In order to select a airfoil, it is important to analyze some characteristics, here it is analyzed only the lift coefficient of the airfoil (C_l) E423, which is usually determined from tests in wind tunnel or in specific software that simulate a wind tunnel (Rodrigues, 2011). Among them, the *XFoil*, used in this work, stands out. The lift coefficient represents the efficiency of the airfoil in generating the lift force. Airfoils with high value of lift coefficient are considered to be efficient for the generation of lift. The C_l is a function of the airfoil model, the Reynolds number and the angle of attack.

2.2 Data Processing

An important point in training an ANN is the preprocessing of the training set, this must be done so that the data does not saturate the network neurons and that data is as uncorrelated as possible. To solve this problem, it must work with a training set that varies its values between -1 and +1 (Haykin, 2001; Freire Jr., 2005). The normalization occurred by dividing each of the values of the data set by their respective maximum value.

The second stage of processing consists of randomly dividing the data into two sets: training and testing, as can be seen in Tab. 1.

Table 1. Database division

DATA SET	DATA AMOUNT
Training set	340
Test set	58

ANN training must be performed with the number of iterations (training times) or the value of the Root Mean Square error (acts as a stopping criterion during training) pre-established. The knowledge of these parameters is important to avoid overfitting (variability of solutions) and underfitting (polarization of solutions) and, consequently, a memorization of the training data set (Freire Júnior, 2005; German et al., 1992 *apud* Nied, 2007).

One way to solve this problem is to use the early stopping rule through the cross validation technique, which consists of dividing the data set into a training set and a validation set. The set of training and use of weight modification, and the set of validation and use to estimate the capacity of data generation during the learning process (Braga *et al.*, 2000).

2.3 Artificial Neural Network

To develop the C_l x α curves for the Reynolds numbers analyzed, a Multi Layer Perceptron (MLP) network architecture was used. 1000 training epochs and only one layer of hidden neurons were used, ranging from 1 to 50 neurons. A representation of the network is shown in Fig. 3. It is important to note that two input neurons (α and *Re*) and one output neuron (C_l) were used.

Figure 3. Inputs and outputs of the ANN

In the network training, the backpropagation error algorithm was used to determine the synaptic weights. Through the backfoward step an error signal calculated at the output is propagated from layer to layer in the reverse direction and at the end we have the weights adjusted and as a function of the error correction, leaving the network response much closer to the desired one. The weights chosen in the training were used to perform the network test (cross-validation) and with this, the data repeatability was analyzed.

The robustness (or repeatability of the results) is a way of analyzing whether ANN has the ability to generalize the result, in other words, to learn about the environment. The analysis should be done comparing the RMS of the training set with the test set and, the less dispersed the values, the more robust the network.

To calculate the RMS error, Eq. (1) is used.

$$RMS = \frac{1}{2N} \cdot \sum_{1}^{N} \sum_{k=1}^{K} \left(d_k - z_k \right)^2 \tag{1}$$

In the Eq. (1) the RMS is the mean square error, N represents the total number of data, K the number of neurons of the output layer, d_k e z_k are the desired responses and the current response of the k-th output neuron, respectively.

If the RMS is considered satisfactory (low value), and the curves C_l X α obtained by simulation (in software that simulates wind tunnel) are close to the curves generated by ANN, the result is generalized. The focus of this work is to make this analysis. A suggestion for the continuation of this research would be the development of a function to determine the Cl x α curve, requiring a larger database of airfoils.

3. RESULTS AND DISCUSSIONS

The results will be divided into two topics: the robustness analysis (repeatability of results) and the presentation of the curve of the lift coefficient.

3.1 Repeatability Analysis

During ANN training, the number of neurons in the hidden layer was changed from 1 to 50 and the RMS calculated for each case according to Eq. (1). This procedure was performed for the training set and for the test set and the lowest RMS value was selected among 1000 times in each hidden neuron change. Thus, an RMS graph of the training X RMS test was developed, as shown in Fig. 4.

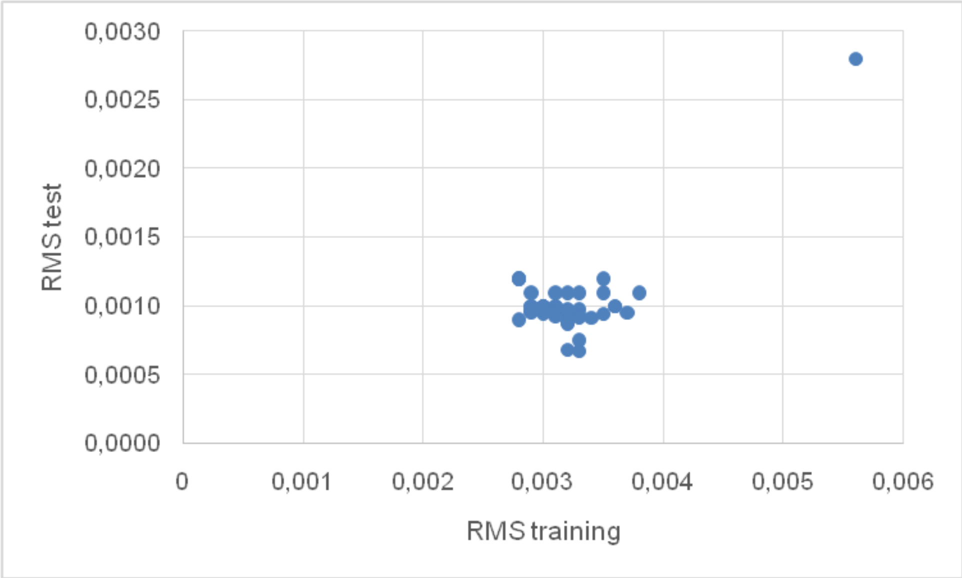

Figure 4. ANN repeatability

It can be seen from Fig. 4 that the RMS values for the training and for the test obtained little dispersion of the results, generating a robust network, that is, with repeatability of the data. However, minimum RMS values were not considered low for ANN applications.

To illustrate the RMS calculation, the graph of the RMS variation with the number of training times was shown in Fig. 5, for a certain amount of hidden neurons (10).

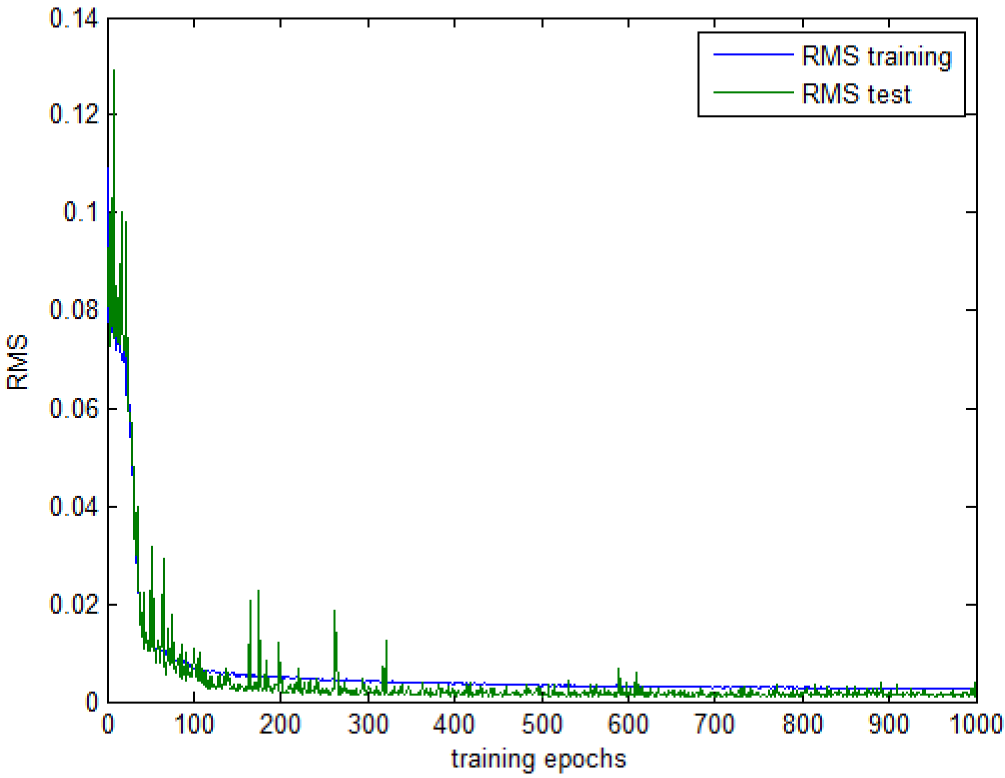

Figure 5. RMS X training epochs for 10 hidden neurons

It can be seen from Fig. 5 that the RMS value stabilizes (approximately constant) in 500 training times, demonstrating that the value of 1000 times was sufficient for the analysis in question.

3.2 C_l x α Curves

For the development of the curves, the values of Re of 1000, 5000, 10000 and 5000 were selected. It is important to note that the E423 airfoil is efficient for low Reynolds values.

To illustrate the comparison of the curves of the E423 airfoil by the curves generated by the profile, Fig. 6 was presented. The result was again chosen for the number of 10 neurons in the hidden layer. In the figure, the dots represent the experimental data and the curves are the results obtained by ANN.

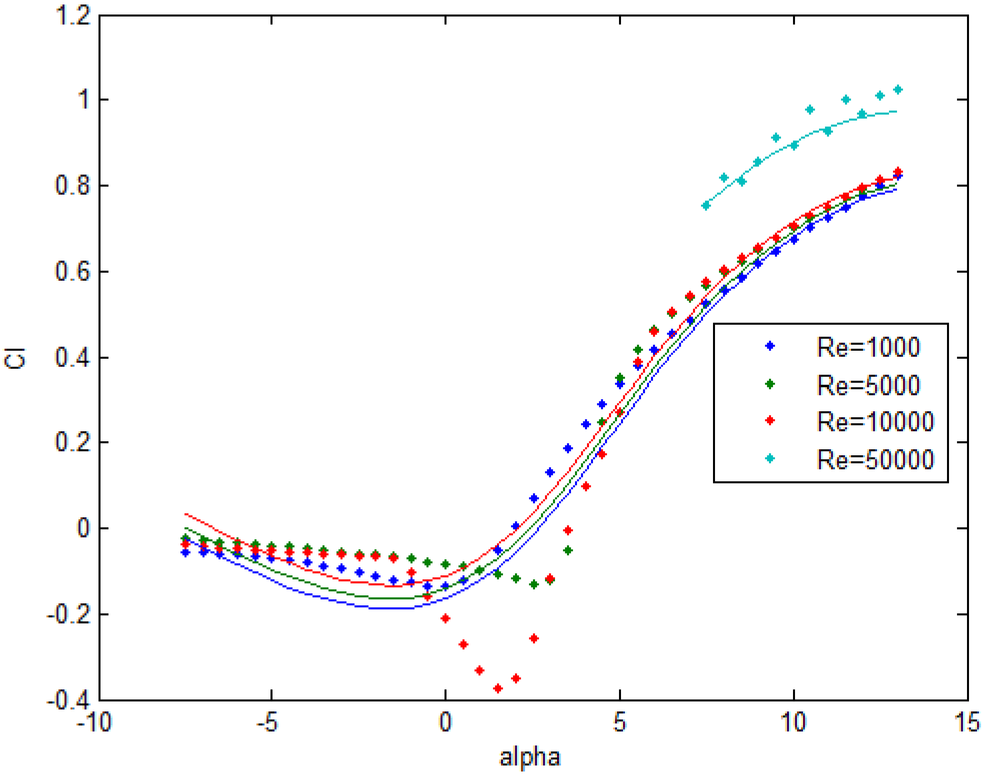

Figure 6. C_l X α for the E423

As can be seen in Fig. 6, some curves represented satisfactorily, although the RMS value is high, mainly for Reynolds equal to 1000 and 50,000. One way to improve these results is to change the network architecture or increase the number of input data.

4. CONCLUSIONS

The work analyzed whether an ANN of MLP architecture is able to represent the lift coefficient curve for the E423 airfoil. In relation to the network, the value of RMS found was high for applications involving neural networks, but the network was robust (with repeatability of the results). Regarding the curves, for some Reynolds values the RNA was able to satisfactorily represent the problem.

One suggestion for improvement for future work is to increase the amount of input data or to change the network architecture by adding more hidden layers or by dividing the problem into modules.

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6. RESPONSIBILITY NOTICE

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