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Prediction of Transition to Turbulence in Airfoils using Artificial Neural Networks

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Abstract. *Transition to turbulence in airfoils plays a critical role in aerodynamic performance and efficiency. This study explores the application of Artificial Neural Networks (ANNs) to predict laminar to turbulent transition in airfoils, using data generated by XFOIL software. XFOIL provides a robust framework for simulating aerodynamic behavior, generating a comprehensive database of airfoil characteristics under various flow conditions. Using this database, ANNs are trained to accurately predict the location of transition to turbulence based on input parameters such as airfoil geometry, Reynolds number, angle of attack and Mach number. The hyper-parameters used to training the ANNs were optimized using grid search. The trained ANNs demonstrate promising performance, achieving high accuracy in predicting transition points across a range of airfoil configurations. This research not only show the efficacy of ANNs in turbulence prediction but also underscores the potential for leveraging computational tools like XFOIL to enhance aerodynamic modeling and analysis.*

Keywords: *ANN, Multilayer Perceptron, Turbulence Transition, Artificial Intelligence*

1. INTRODUCTION

The prediction of transition to turbulence in airfoils is a fundamental aspect of aerodynamic design and performance optimization in aviation and aerospace engineering. Transition from laminar to turbulent flow significantly affects lift, drag, and overall aerodynamic efficiency of airfoils, influencing crucial factors such as fuel consumption, maneuverability, and structural integrity of aircraft. Traditional methods for predicting turbulence transition involve complex mathematical models and empirical correlations, often limited by computational costs and accuracy (Schmid *et al.*, 2001). However emerging simulation tools, including neural networks, offer novel methodologies for forecasting system performance. These tools embody a revolutionary computing paradigm inspired by the brain's parallel architecture.

A neural network is a computational model inspired by the structure and function of the human brain. It consists of interconnected nodes, called neurons, organized in layers. Each neuron processes input data, applies weights to these inputs, and uses an activation function to produce an output. Neural networks are designed to learn from data through a process called training, where they adjust their weights based on the error between predicted and actual outcomes. Recent advancements in Artificial Neural Networks (ANNs) offer a promising alternative approach, leveraging the power of machine learning to analyze large datasets and extract intricate patterns in aerodynamic behavior (Brunton *et al.*, 2020; Racca *et al.*, 2023; Beiki and Kamali, 2023).

This study focuses on the utilization of ANN based model for predicting the location of turbulence transition in the airfoil upper and lower surface, employing XFOIL as a computational tool to generate an extensive database of airfoils characteristics across a range of flow conditions. XFOIL is a popular software package for airfoil analysis and design proposed by Drela (1989), and provides a robust platform for simulating aerodynamic performance, enabling the generation of extensive datasets necessary for training ANNs. By harnessing the data generated by XFOIL, ANN based model can be trained to accurately predict the onset of turbulence based on input parameters such as airfoil geometry, Reynolds number, and angle of attack. The trained neural networks offer the potential for rapid and precise turbulence transition prediction, facilitating enhanced aerodynamic design and optimization processes.

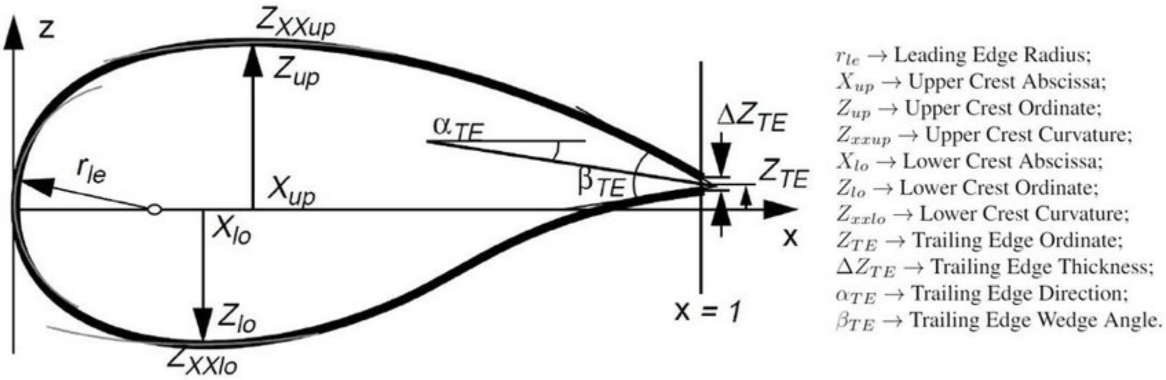

Figure 1. Parsec parameters for an airfoil representation (Sobieczky, 1999)

2. Estimation of the turbulent transition location using an MLP

2.1 Dataset preparation

The PARSEC polynomial parameterization was used to generate airfoil geometries from eleven geometric features (Sobieczky, 1999). These eleven parameters are used as the control variables to compute the airfoil shape, see Figure 1. PARSEC parameters for a specific airfoil are derived by fitting two polynomials to the known geometric characteristics: one for the upper surface and another for the lower surface. These polynomials are defined by:

$$z_u = \sum_{i=1}^{6} a_i \cdot X^{i-0.5}, \tag{1}$$

for the upper surface and

$$z_l = \sum_{i=1}^{6} b_i \cdot X^{i-0.5}, \tag{2}$$

for the lower surface. Where a_i and b_i are coefficients driven by the eleven control variables, see Syafei *et al.* (2022) for more details.

A fast numerical way to estimate the laminar to turbulent transition point of an airfoil is through the XFOIL software. This software uses a panel method with Karman Tsien compressibility correction, coupled with a viscous/inviscid interaction method that calculates the viscous effects of the boundary layer as well as the transition equations (Drela, 1989). The results obtained with XFOIL show great agreement with experimental data for subsonic speeds and low angles of attack, and can be used here.

In our endeavor to train a multilayer perceptron (MLP) for predicting airfoil turbulence transition, we get a large dataset generated by XFOIL. The critical N = 9, which is the default for XFOIL. This dataset was obtained using the 12 Parsec parameters to characterize the airfoils, the angle of attack, the Reynolds and Mach numbers as inputs, and the transition to turbulence location of upper and lower surfaces of the airfoil as outputs. To train the neural network, the coordinates of 1500 airfoils available in the University of Illinois at Urbana-Champaign (UIUC) database were used (Selig, 2024). PARSEC parameters for each airfoil in the database were obtained using a reflective confidence region algorithm. For the aerodynamic parameters we varied the angle of attack from $\alpha = -18$ to $\alpha = 18$ with 1 of increment, we evaluated 6 Reynolds numbers based on the airfoil chord from $2 \cdot 10^5$ to $2 \cdot 10^6$ with uniform logarithmic spacing, and four Mach numbers: $M = (0, 0.1, 0.2, 0.3)$. The training data generation procedure resulted in a training set with 1116000 instances, where the combinations of the input parameters which XFOIL did not converge were discarded.

2.2 ANN architecture

The chosen ANN architecture was the multi-layer perceptron (MLP) in a supervised and regression modes, which is an ANN whose neurons are arranged in several layers: an input layer, one or several hidden layers, and an output layer. Due to their dense connectivity between successive neuron layers, MLPs have been extensively adopted to find complex interrelation between multiple input variables and one or multiple output variables. In MLPs the information is transmitted feed-forward, and therefore, they are memory-less. This is a desirable characteristic in our case since the successive input configurations may not be correlated. In addition to our case, the hyperparameter tuning and the parameter optimization can be relatively straightforward and intuitive, making them an efficient tool in many applications. The complexity of

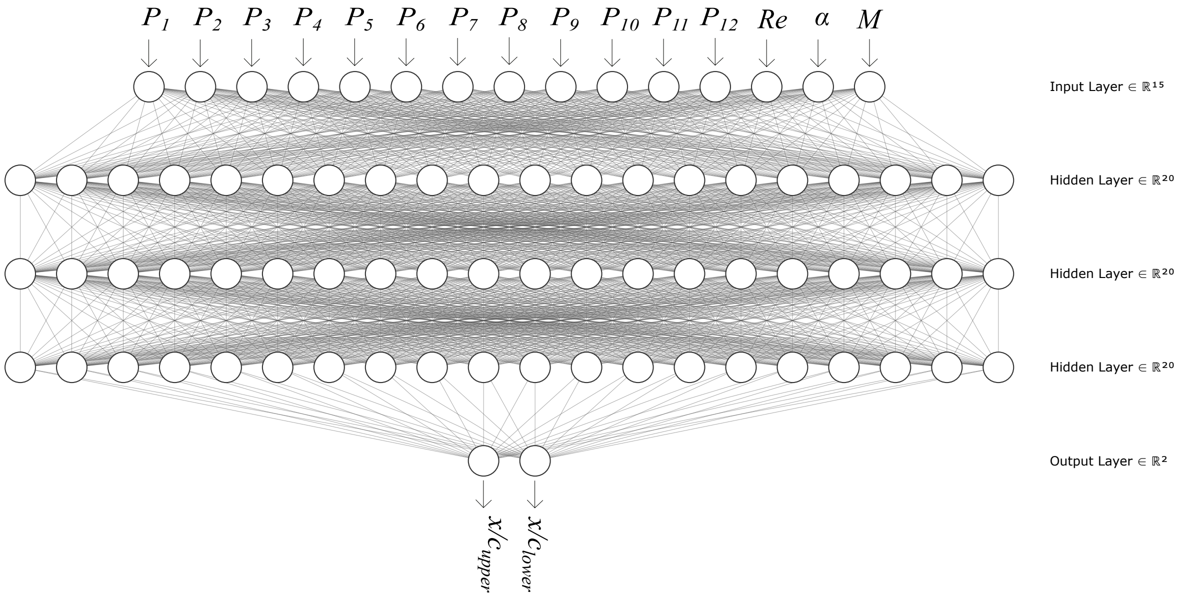

Figure 2. Architecture scheme of the Multilayer Perceptron.

a grid search is exponential with the number of hyperparameters, thus often more complex methods must be used, for instance, Bayesian optimization.

In Figure 2, we show the general block diagram of the employed MLP. As can be seen, a single MLP is used to simultaneously predict the upper and lower locations of the turbulence transition points. The network has 15 input parameters, corresponding to the 12 PARSEC parameters, the Reynold's number, the attack angle and the Mach number. We considered MLPs with 1, 2, or 3 hidden layers with neuron numbers ranging from 20 to 1000. Regarding the activation function, preliminary tests revealed that rectified linear unit (ReLU) outperformed other widely adopted activation functions, such as logistic or hyperbolic tangent. Therefore, we focused in MLPs with ReLU activation function.

In addition the complete set of data was split into three blocks: 75% of the provided data used for training, 15% for validation and 15% for testing. The synaptic weights and biases were initialized randomly using a zero-mean Gaussian distribution. The weights were updated using the Rossemblat error back-propagation method in association with the Adam optimizer.

Scikit-learn was used to implement our ANN based model, leveraging its comprehensive machine learning library for efficient development and training. Scikit-learn provides a user-friendly interface and robust functionalities for constructing MLPs with customizable parameters such as the number of layers, neurons per layer, and activation functions. It also facilitates preprocessing tasks like scaling input data and splitting datasets for training and testing. By harnessing scikit-learn's capabilities, we were able to swiftly deploy and optimize our MLP model to analyze complex patterns and relationships within our data, ensuring accurate predictions and insights.

3. Results

3.1 Model validation and hyperparameter tuning

Figure 3(a) shows the RMS of the validation error in terms of the neurons number in each hidden layer for three different configurations, 1, 2 and 3 hidden layers. We can notice that all the traces have a decreasing tendency, with a decay more prominent for low neuron counts, which indicates a biasing issue, in other words, a model too simple. There is no indication of overfitting for the considered configurations, this can be attributed to the large number of dataset used here, 1160000 entries. When comparing the traces for different numbers of layers, we can notice that as the number of hidden layer increases, the RMS of the prediction error tends to decrease. The traces also show a instability in the prediction error with the increase of the neurons number for all configurations, but more pronounced for 2 and 3 hidden layers. These can be explained by the increase of the number of parameters for higher number of hidden layers and neurons, which makes more probable to converge to a local minimum, instead to the global one. This can be minimized performing multiple independent training runs, averaging the results.

The predicted transition locations x/c in the upper and lower surfaces values in terms of the simulated values for the validation subset, employing a neural network with 3 hidden layers composed of 500 neurons each, is show in Figure 3(b). We can notice that most points are concentrated around the ideal straight line, with unit slope, through zero, indicating that the MLP was well trained and presents impressive prediction results for both cases, x/c in the upper and lower surfaces. It can be seen that x/c in the lower surface presents a greater dispersion of points, when compared to the transition location

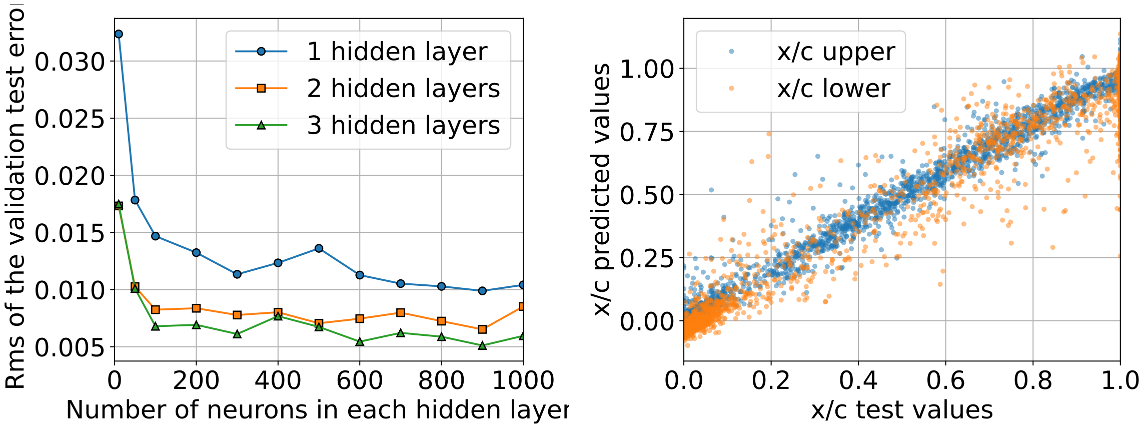

Figure 3. (a) RMS of the validation error in terms of the neurons number in each hidden layer for three different configurations; (b) Predicted transition location x/c upper and lower surface values in terms of the simulated values for the validation subset, employing a neural network with three hidden layers composed of 500 neurons.

at the upper surface, which is expected for most asymmetric airfoils. Perhaps better results could be obtained by creating an MLP dedicated for each of those parameters.

3.2 Prediction error analysis

The prediction error for transition location x/c of upper and lower surface of the airfoil and the associated hystogram are shown in Figure 4(a) and (b), respectively. As can be expected from Figure 3(b), the prediction error represented in Figure 4(a) is concentrated in the $[-0.2, +0.2]$ range for both outputs. It is worth noting that these errors present higher values in the leading edge of the airfoil for the lower surface. A better knowledge on the error distribution can be obtained from the histograms shown in Figure 4(b). We can notice that the dataset for the x/c in the upper surface is more dispersed in an interval around zero but has fewer outliers, while most of the dataset for the x/c in the lower surface points are concentrated in a smaller interval around zero, but with a greater number of outliers.

4. Conclusions

This study highlights the significant advancements achieved in predicting laminar-to-turbulent transition in airfoils through the application of Artificial Neural Networks (ANNs). By leveraging the comprehensive dataset generated from XFOIL simulations, the research has demonstrated that ANNs can effectively model and predict the complex transition behaviors under varying aerodynamic conditions. The optimization of hyper-parameters via grid search further enhanced the accuracy of these predictions, confirming the potential of ANNs as a powerful tool for aerodynamic analysis. This work not only validates the efficacy of ANNs in turbulence prediction but also emphasizes the valuable role of computational tools like XFOIL in advancing aerodynamic research and improving airfoil performance. Moving forward, the integration of such predictive models could lead to more efficient aerodynamic designs and a deeper understanding of flow dynamics, ultimately contributing to innovations in aircraft design and performance.

5. ACKNOWLEDGEMENTS

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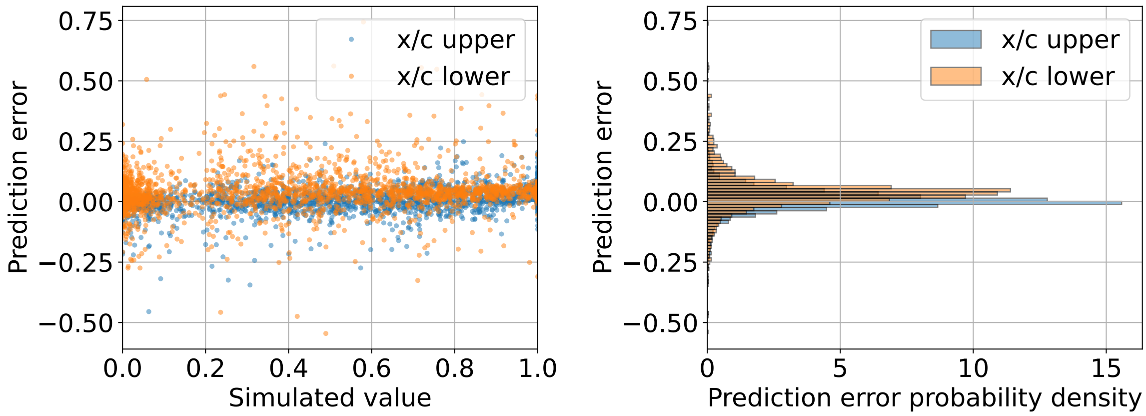

Figure 4. (a) Prediction error for transition location x/c of upper and lower surface of the airfoil; (b) The associated hystogram.

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