Efficient Prediction of Coefficients and Performance of Airfoil Using ANN

Harsh Bhutra[1], Chandan K.[2], T. V. Smitha[2]

[1]Department of Electronics and Communication Engineering, Amrita School of Engineering, Bengaluru, Amrita Vishwa Vidyapeetham, India.

[2]Department of Mathematics, Amrita School of Engineering, Bengaluru, Amrita Vishwa Vidyapeetham, India.

*Corresponding author: tv_smitha@blr.amrita.edu.

***Abstract*— The foremost step while designing an aerodyne vehicle is the selection of the right airfoil as per the flight condition. To determine the correct shape of the vehicle, measuring aerodynamic coefficients is the most essential part. According to the accuracy level, numerous methods exist to calculate these coefficients. The information about different NACA airfoil sections is in huge demand, although the aircraft engineers primarily use NASA's supercritical airfoil sections, as the NACA airfoils are still extensively used to design propellers, aircraft wings and they also find their way in many other aerodynamic applications. In this paper, computer-based software is used to collect data on these coefficients and an attempt to predict the best set of coefficients is tried by applying Artificial Neural Networks (ANNs) for different sets of Reynolds number. The code implements a simple feed-forward neural network for a regression problem using MATLAB.**

Keywords—NACA airfoil; Machine Learning; Artificial Neural Network; Regression Learner; Aerodynamics; Matlab

I. Introduction

Aerodynamics has always been one of the most interesting fields of study, even in the modern world. Among its many important subfields is the study of airfoils [1]. An airfoil gives the most advantageous ratio between drag and lift in flight. It is basically a cross-sectional shape mapped out with a curved upper surface, which is also known as the chamber and a flatter lower surface. This inimitable cross-sectional shape is asymmetrical and is responsible for generating Lift by manipulating Bernoulli's principle and the third law of motion given by Sir Isaac Newton. Within the aerodynamics of an aircraft, an airfoil design establishes a crucial aspect. There are four different forces that are acting on an airfoil. They are known as Lift, weight, drag and thrust. The force acting perpendicular with respect to the motion of the airfoil is known as Lift, whereas, the force acting parallel to the motion of the airfoil is known as Drag [2]. Throughout the design process of an aerospace vehicle, an aeronautical engineer enlists the airfoil's geometric properties to compute initial coefficients of Lift, drag and moment, as well as to determine the aerodynamic center, center of pressure and other relevant parameters. At higher Reynolds numbers when the airflow becomes turbulent, the amount of drag also increases drastically whereas the amount of Lift is directly proportional to the flow pattern. The efficiency at higher altitudes is comparatively much lower than that on the lower altitudes. Any flying machine which is operating at around 66000 ft-165000 ft will find less dense air and a low pressure around it [3]. It will also encounter a much lower air viscosity, limiting the tip speed for a given Mach number. Taking fluid dynamic forces into consideration, turbulent inflow is a fluid governance categorized by disarrayed, stochastic property variations. Including low instigation prolixity, high instigation convection in space and time. The performance of the propellers is generally calculated by Blade Element Momentum theory (BEM) because there's a low computational cost involved [4].

It's assumed that about 50 years ago NACA series of airfoil sections came into existence. Numerous software programs were developed in the 70's era to fabricate and predict the coordinates for airfoils of all kinds of thickness and thickness distribution, or camber or position of camber in the NACA airfoil series [5]. In this paper, one such computer program called "XFLR 5" is used to prepare the dataset, which is detailed in the next section.

An idea of a nonlinear multidimensional singular integral equations is responsible for determining the coefficient response of pressure and velocity around the airfoil. The solution for the equation is gathered from the newly designed aerodynamic problems. These solutions help in identifying specific behavior of the airfoil under different conditions and such behaviours of the airfoil play a pivotal role in the design of the modern aircrafts with very high speeds. One of the most common applications of these airfoils is to determine coefficient fields of velocity and pressure around an aircraft an aircraft [6]. There are many pre-existing software programs that are based on artificial intelligence and are in the field of fluid mechanics. Which include incompressible flow and steady state. Numerous studies are being conducted to increase the precision in prediction in the area of flow fields and aerodynamic force coefficients of airfoils [7].

In this paper, a comparison of the performance of different airfoils have been performed with the help of various values of Cl and Cd, i.e., coefficient of lift and coefficient of drag respectively. The values of Cl and Cd of a NACA airfoil dataset deliver valuable information about the characteristics of the aerodynamics and the performance of airfoil. From the values of Cl and Cd numerous important parameters can be derived. For instance, the amount of lift that is been produced per unit drag can easily be calculated by taking the ratio of Lift-to-Drag. If the Cl values are plotted against that of Cd the resulting graph would create a drag polar. Angle of attack range which is an important parameter in determining the airfoil's operational envelope can also be calculated by the values of Cl and Cd at different angles of attack [8]. This range mostly lies where the airfoil maintains a desirable Lift-to-Drag ratio. Nevertheless, Cl and Cd values at different angles of attack can also help to determine the stall characteristics of the airfoil. This stall occurs whenever the angle of attack increases beyond a threshold leading to the decrease in the lift and increased drag [9]. Understanding this behavior of the airfoil is very important so as to assess the airfoil's performance limit and flight safety. Moreover, the values of Cl and Cd indicates the two forces related to the airfoil, namely, lift force and drag force [10].

To summarize, the different values of Cl and Cd for various NACA airfoil provides us the essential drive to study the aerodynamic performance, efficiency, and operational limits of the airfoil, making the information collected by these values very crucial for the design of an air-vehicle, its performance evaluation, and optimization to achieve desired flight characteristics [10]. The values of Cl and Cd when compared under certain conditions, such as at a certain Reynolds number provides a perception about the airfoil's behavior for that particular flight regime.

This paper aims to collect data for different NACA 4-digit series corresponding to different Reynolds number and then filter that data and train an artificial brain using Artificial neural network model in machine learning to the best data point while plotting different other essential graphs and histograms for the particular dataset. The remainder of this paper is organized as follows: section 2 briefs about the technique used and the work done related to the collection of the data set. Section 3 discusses about the result and discussion and the last section, section 4 presents with the conclusion.

II. DATA PREPARATION

Owing to the large application of the NACA airfoil, a dataset of NACA 4-digit series have been generated using a software called as XFLR5. The software is basically designed for the 4- or 5- digit NACA foils and allows the user to choose the number of Panels of their choice. As soon as you provide the digits of the airfoil and the number of panels, the software plots a two-dimensional graph of all the points that a particular airfoil consists of as described in [11], [21]. Moreover, the software also gives plenty options to perform different types of analysis on those points. Which are completely personalized, as in the user can set alpha values, Cl values or get the output based on a particular Reynolds number. The output is plotted on various different graphs.

The proposed dataset comprises of five inputs, namely alpha, camber, position of camber, thickness and Reynolds number and two outputs, namely coefficient of lift and coefficient of drag for different thickness ranging from 0.06 to 0.24 and different alpha values, Table-I shows a few values from the same. The data set contains 9 different NACA airfoils, NACA 0012, NACA 0008, NACA 0024, NACA 0018, NACA 2414, NACA 0015, NACA 0006, NACA 0021, NACA 0010, with a 6187 total number of entries which are calculated over 135 different possible conditions for flight. Making a total of 835245 samples in the data set.

Table I: Span of Airfoil parameters

Alpha	Camber	Position of camber	Thickness	Reynolds number
-5 - 20	0 - 2	0 - 4	0.06 - 0.24	0.001e+06 – 50.0e+06

III. DATA PREPROCESSING

The ANN model requires three step processing of the data before the data is actually been fed to an ANN, these steps are: Reformatting the data, cleaning of the data and data processing. A script was written in MATLAB which imports all the data-files, stacking them all together in the required arrangement. While simultaneously cleaning the data. From the total of 6187 data entries 60% of the data is used for training the model, 20% is used for validation and the remaining 20% of the dataset is used for testing. The script first loads the data and perform data normalization which bring the mean of the data to a value of zero and standard deviation value to one, this helps us ensure that all the data are on similar scale. This is followed by splitting the data set and training of the data. For this problem the learning rate is set to 0.01 which can be changed according to the requirement and the complexity of the data. Furthermore, the neural network model is created which is further followed by training the neural network, and the maximum number of training epochs is set to 1000 with a tolerance of 10 consecutive validation failures before stopping training. Furthermore, the size of hidden layer is set to 10.

IV. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Network, as depicted in Figure 1, is also known as the artificial brain as it learns by itself. It successfully, up to a great extent, is able to simulate the way a human brain processes and analyze any information through a mesh of interconnected multi-layered neurons [12 - 13]. For instance, the proposed methodology is using a three-layered neural networking system. These three layers are: input layer, hidden layer and output layer [14]. The determination of the response of a neuron is dependent on a function known as activation function *f(v)*. This activation function defines a particular output based on the input that's provided. Sigmoid function is the most widely used function. It is a bounded, monotonic increasing function which provides a non-linear response which map a network to any non-linear process [15]. The sigmoid function is given by:

$$f(v) = \frac{1}{1+e^{-v}}$$

Using a linear activation function, for the output layer in a regression task, means that the output of the particular network is nothing but simply a weighted sum of the inputs, without applying any non-linearity to it [16], [17].

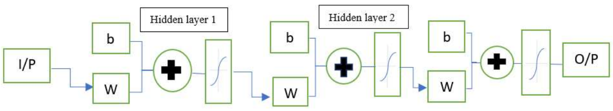

Figure 1. Flowchart representing Artificial Neural Network

V. RESULTS AND DISCUSSIONS

The MATLAB script trains the neural network using the Levenberg-Marquardt backpropagation algorithm and the calculations are been done as per MEX algorithm [18]. The script runs till a maximum of 1000 epochs and a maximum of 10 validation failures are allowed before stopping the execution. The entire training process is recorded in a variable named 'tr'. To make the predictions on the training, validation and testing sets the script uses the trained network. The script then proceeds further to calculate several other important performance metrics such as, Mean Absolute Error (MAE), Coefficient of Determination (R^2), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) for all the sets. All these performance matrices signify how well the network has performed on each data-set. For better performance the value for MAE, RMSE and MSE should be as lower as possible [19], whereas, the value for R^2 should be as close to 1 as possible, as it measures the proportion of variance in the target variable that is predictable from the input, the results of which are shown in Table II. The script then plots a histogram to visualize the distribution of errors, Figure 2. This histogram is called error histogram. The Figure 3, plots the training state, wherein the gradient, Marquardt parameter 'Mu' and the validation checks. Furthermore, the dataset was also tested using regression learner, it is a form of predictive modelling approach which works on analyzing the relationship between a dependent variable and an independent variable across the dataset. It could be done by feeding the data into an in-built MATLAB application called Regression Learner [20] and the output is shown as per Figure 4. Figure 5, illustrates the performance of all the datasets with respect to the best point for the entire dataset. At last, the script proceeds further and tries to plot a correlation matrix with respect to all the features. The correlation matrix, as shown in Figure 6, shows the correlation coefficients between different pairs of variables in a dataset and hence, aims to signify the relationships between all of them.

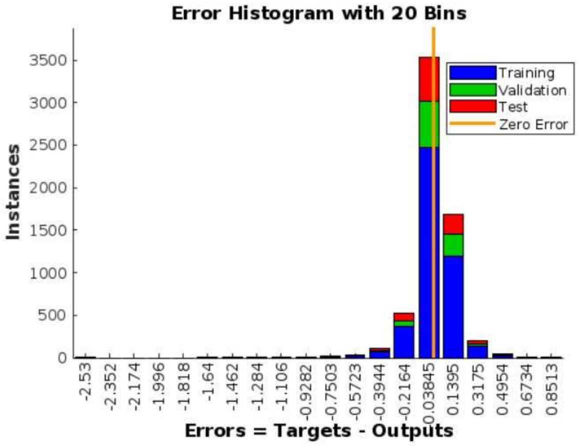

Figure 2. Error Histogram

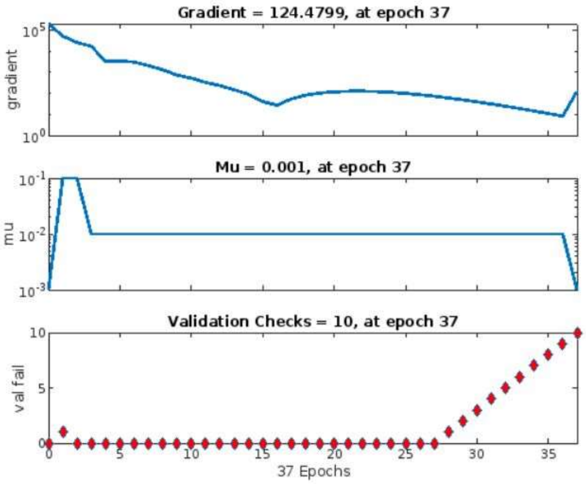

Figure 3. Gradient plot, Marquardt parameter plot and plot for validation checks

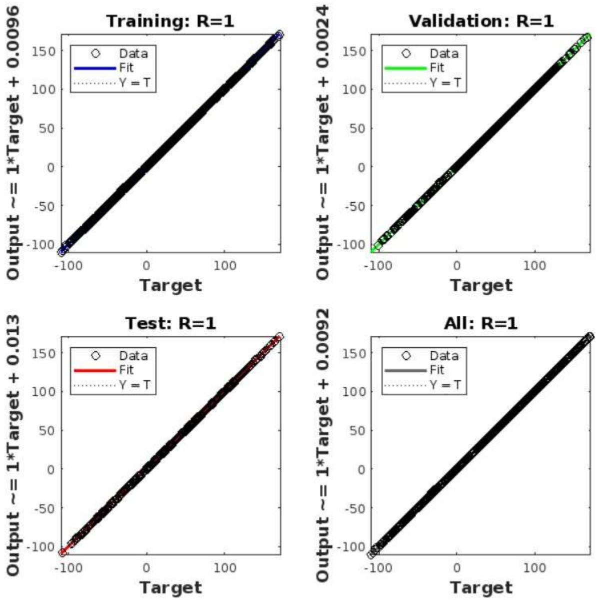

Figure 4. Regression plots for training, testing, validation and the entire dataset

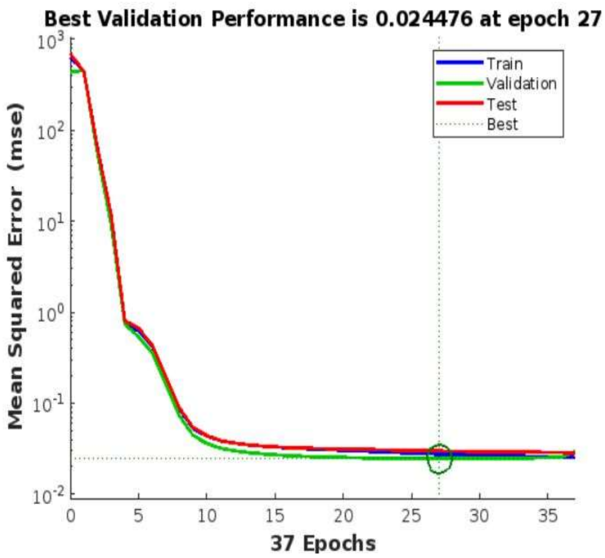

Figure 5. Performance graph

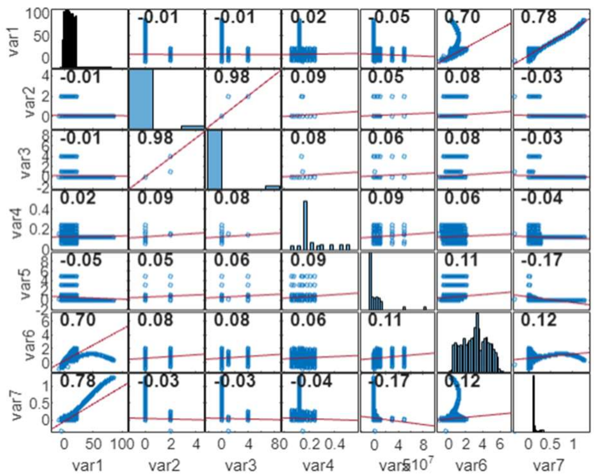

Figure 6. Correlation Matrix

Table II: Error and R^2 values of the dataset

	MSE	RMSE	R^2	MAE
Training	0.0012236	0.03498	1	0.022866
Validation	0.12823	0.35809	0.99997	0.10412
Testing	38.6701	6.2185	0.99282	1.1604

VI. CONCLUSION

There are several distinct reasons that contributed to ANN's exceptional success in this study. The use of the computer-based programme XFLR5 for data production constitutes a major improvement, first and foremost. Compared to conventional manual approaches, this software probably offers more precise and thorough data, offering ANN a substantial dataset to work with. Additionally, it is crucial to choose ANNs for modelling the performance of the airfoil. ANNs are well suited for the sophisticated aerodynamic aspects of NACA airfoils because they are excellent at capturing detailed patterns and correlations within data. A key factor is the variety of the training data, which consists of NACA 4-digit airfoils with various Reynolds numbers. This broad dataset improves ANN's capacity to generalize across various flight situations, enabling more accurate predictions of coefficients like Cl and Cd. In short, ANN's accomplishment in this work highlights the effectiveness of data-driven, ANN-based methodologies in achieving more accuracy and precision in the analysis of NACA airfoils, with implications for enhancing the general comprehension and computations in studies connected to aerodynamics.

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