International Journal of
Science and Engineering Investigations vol. 1, issue 1, February 2012

Application of Artificial Neural Network for the Prediction of Aerodynamic Coefficients of a Plunging Airfoil

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Abstract- Neural networks were used to minimize the amount of data required to predict the aerodynamic coefficients of an airfoil oscillating in plunging motion. For this purpose, series of experimental tests have been conducted on a section of a 660kw wind turbine blade. Two MLP (multi layer perceptron) and GRNN (general regression neural network) were trained using experimental data of the airfoil at various conditions. Results showed that with using only 50% of the acquired data, the trained neural networks were able to predict accurate results with minimal errors when compared with the corresponding measured values. Moreover, these methods can predict the aerodynamic coefficients of the plunging airfoil at different oscillation frequencies, amplitudes, and incidence angles. Therefore with employing this trained networks, the aerodynamic coefficients are predicted accurately with minimum experimental data; hence reducing the cost of tests while achieving acceptable accuracy.

Keywords- *Neural Network; MLP; GRNN; Plunging; Wind turbine.*

I. INTRODUCTION

The methods for predicting unsteady flows and dynamic stall used by the industry are largely based on empirical or semi-empirical approaches that are fast and relatively accurate where non-linear effects are not too great. Increased development in aircraft and wind turbine aerodynamics creates demand for more detailed information of the non-linear unsteady loads, dynamic response, and aero-elastic stability, caused by the dynamic motions, including dynamic stall effects [1].

Wind turbine or helicopter rotor blade sections encounter large time dependent variations in angle of attack as a result of control input angles, blade flapping, structural response and wake inflow. In addition, the blade sections encounter substantial periodic variations in local velocity and sweep angle. Thus, unsteady aerodynamic behavior of the blade sections must be properly understood to enable accurate predictions of the air loads and aero-elastic response of the rotor system [2]. Most of the angle of attack changes that the rotor blades encounter are due to the variations in flapping and elastic bending of the blade, i.e., plunging type forcing [3].

In order to reduce measurement points and wind tunnel time, neural networks are used for predicting aerodynamic coefficients. Neural networks represent a powerful data processing technique that has reached maturity and broad application and can accurately predict both steady and unsteady aerodynamic loads while capturing the essential fluid mechanics mathematically.

The ability of neural networks to accurately learn highly nonlinear, multiple input/output relationships makes this a promising technique for modeling the aerodynamics test data. There has been considerable interest in the aeronautical applications of neural networks. Schreck and Faller successfully trained a neural network to predict the unsteady pressure variations on a pitching wing [4]. Other applications have since been reported for characterizing flight test data [5,6].

In this study extensive low speed wind tunnel tests were conducted to study the unsteady aerodynamic behavior of an airfoil sinusoidally oscillating in plunge. The experiments involved measuring the surface pressure distribution over a range of amplitudes and oscillating frequencies at three different mean angles of attack of 5º, 10º and 18º. For all oscillation cases, Reynolds number was fixed at of 0.42×10^6. The unsteady aerodynamic loads were calculated from the surface pressure measurements, 64 ports, along the chord for both upper and lower surfaces of the model [7]. The plunging displacements were transformed into the equivalent angle of attack. Note that in a plunging motion, the model moves vertically up and down inside the tunnel test section. The neural network was used to increase the resolution of observation to predict the aerodynamic coefficients at various conditions.

II. EXPERIMENTAL APPARATUS

All experiments were conducted in the low speed wind tunnel in Iran. It is a closed circuit tunnel with rectangular test section of $80\times80\times200cm^3$. The test section speed varies continuously from 10 to 100 m/sec, at Reynolds number of up to 5.26×10^6 per meter. The model considered in the present study has 25cm chord and 80cm span and is the critical section of a 660kW wind turbine blade. This model is equipped with 64 pressure orifices on its upper and lower surfaces. The pressure ports are located along the chord at an angle of 20 degrees with respect to the model span to minimize disturbances from the upstream taps, Fig. 1.

Data were obtained using sensitive pressure transducers. Each transducer data was collected via a terminal board and transformed to the computer through a 64 channel, 12-bit Analog-to-Digital (A/D) board capable of an acquisition rate of up to 500 kHz. Dynamic oscillatory data presented here are an average of several cycles at a sample rate based on the oscillation frequency. Raw data were then digitally filtered using a low-pass filtering routine. The oscillation amplitude was varied sinusoidally as $h = \bar{h}\sin(\omega t)$, where ω is angular velocity and $\bar{h}$ is the amplitude of motion. The plunging displacement was transformed into the equivalent angle of attack using the potential flow transformation formula, $\bar{\alpha}_{eq} = ik\bar{h}$, where $\bar{\alpha}_{eq}$ is in radians and $\bar{h}$ has been nondimensionalized with respect to the model semi-chord. The mean angle of attack was, of course, added to the equivalent angle of attack [8].

III. NETWORKS ARCHITECTURE

The artificial neural networks algorithm have been developed using aerodynamic coefficients of the airfoil at certain conditions, from experimental data. The networks use this information as their training data and their weights were adjusted to minimize the error between the predicted results and the experimental data. Then, once the desired accuracy has been achieved, the trained network was used to predict the aerodynamic coefficients at different conditions. Two MLP and GRNN networks were trained. These networks, after training, use instantaneous angles of attack for both upstroke and down stroke motions with certain frequency and amplitude of oscillation as inputs while their outputs are the aerodynamic coefficients at the related angles of attack.

The MLP network is of type "cascade-forward back propagation network" which consists of 2 hidden layers and 3 neurons using "tansig" and "satline" activation functions. Training methodology was the Levenberg-Marquardt algorithm, which is an implementation of a quasi-Newton method, with variable learning rate. This algorithm ensures convergence, as in the steepest descent method, and has good performance, as does the Gauss-Newton algorithm.

IV. RESULTS AND DISCUSSIONS

The unsteady aerodynamic loads were calculated from the surface pressure measurements, 64 ports, along the chord for both upper and lower surfaces of the model. The unsteady lift coefficients are shown for three different mean angles of attack of 5, 10, and 18 degrees and for reduced frequencies of 0.03, 0.045, and 0.06 for constant plunging amplitude of ±15cm. An arrow gives the direction of each loop. The corresponding static values are shown for comparison.

Figure 2 shows variations of cl with the equivalent angle of attack for three different mean angles of attack. In the linear part of the static cl values, Fig. 2a, the slopes of the hysteresis loops tend to follow the steady data. The directions of the hysteresis loops are counterclockwise for higher reduced frequency cases, k=0.045 and 0.06, which means the lift in the upstroke curve lags the static data while in the down stroke portion it leads the corresponding static values. For the lower reduced frequency, k=0.03, however, the hysteresis loop shows a "figure eight" shape. This may indicate that there is an undershoot of the lift in the upstroke part of the curve at high equivalent angles of attack, while at the low equivalent alpha, the reverse is true, overshoot. Consequently there is a crossover point, the upstroke and down-stroke lift coefficients are the same, for a specific induced angle of attack, α=4º. As it is seen from Fig. 2a, the effect of increasing the reduced frequency is to increase the amplitude of the induced alpha while widening the hysteresis loops. Looking at Fig. 2b, it is seen that plunging the airfoil near its static stall angle, $\alpha_{static-stall} \approx 11^\circ$, causes different trends in the dynamic lift coefficients. At a reduced frequency of 0.03, the direction of the loop is clockwise but at reduced frequencies of 0.045 and 0.06 the direction of the cl hysteresis loops changes from lag to lead with crossover points near α=9º for k=0.045 and about α=8º for k=0.06. In this region, increasing the reduced frequency induces higher maximum lift value and postpones the stall to higher equivalent angle of attack. Plunging the airfoil with a mean angle of 18º or in the post stall region, causes the hysteresis loops of cl to become clockwise for all three reduced frequencies, Fig. 2c. This is due to the influence of the different time lags and the vortex shedding. As a fact, when oscillating the airfoil with lower mean angles, the direction of the hysteresis loops are strongly affected by the trailing edge wakes and the lag of pressure distribution. However, when oscillating with higher incidence, there exist a separated flow region behind the airfoil and the moving wall effects along with the vortex shedding play an important role in the trends of the loops.

The neural networks are used to minimize the amount of data required to predict the aerodynamic coefficients of the airfoil. For training the networks, the input data were included of sets of instantaneous angle of attack, reduced frequency, and amplitude of motion for each case. Related Aerodynamic coefficients were considered for the output ones. The validity of the applied method was investigated at several cases to ensure its effectiveness to provide desired results with permissible error.

To ensure that the weights in the neural networks have been correctly set and the corresponding outputs are sufficiently reliable, a validation process is applied after training has been completed. The set of known inputs with their desired output needs to be divided into two distinct sets. The first set is the training set and is used throughout the training period to adjust the weights to the appropriate values. The second set is referred to as the validation set and is used to test the network. Once the values of the training set have been determined, the inputs from the validation set are inserted into the network and the output of the network is compared with the target values in the validation set.

Figure 3 displays comparison between the expected data and their predicted ones for the lift coefficient from both

GRNN and MLP neural networks. For the GRNN, various spread parameters [9], σ, are used. The model is set to an incidence angle of 5 degrees and oscillated with a plunging amplitude of ±5cm at a frequency of 2.22Hz (k=0.04). For training the network, three sets of data, related to various amplitudes and frequencies, but with mean angle of attack of 5 degrees are used. Note that separate networks are used for upstroke and down-stroke portions of the hysteresis loops. It is seen that there is a good agreement between results of the Artificial Neural Networks and the experimental data. It is shown that for the GRNN, the spread parameter has an important role in predicting the results of this network, Fig. 3a. The values of 0.05, 0.5 and 0.9 are selected for the spread parameter. It is seen that for the case of σ=0.5, the prediction of the network is slightly better than the other values. It can also be seen from Fig. 4 that using the value of σ=0.5 has a minimum percent of average error. The MLP network shows better results than the GRNN, with error of only about 0.02%, Fig. 3b. In contrast to the GRNN, two ends of the upstroke and down-stroke portions of the hysteresis loop are well predicted by the MLP network, Fig. 3b. However, fast training is an outstanding characteristic of GRNN which allows engineers to deal with time variant systems. The variation of error with angle of attack in the GRNN for the case of σ=0.5 is shown in Fig. 5. It is seen that the error is higher at two ends.

In Fig. 6, the model is set to an angle of 10 degrees, the oscillation frequency is 3.33Hz and the amplitude of the motion is ±5cm. For training the network, four sets of data, related to various amplitudes and frequencies, but with the same mean angle of attack are used. The results are only for the MLP network which shows a good agreement with the experimental data. The location of the crossover point (mentioned before in Fig. 2) is well also predicted. However, the GRNN was poor in predicting this location.

In Fig. 7, the model is set to an incidence angle of 18 degrees (post stall region), the oscillation frequency is 2.78Hz and the amplitude of motion is ±10cm. The variation of the lift coefficient with equivalent angle of attack is shown from both GRNN and MLP neural networks and is compared with the experiment. It is seen that employing the trained GRNN, the lift coefficients are predicted accurately with average errors of about 1.7% for both upstroke and down stroke motions of the airfoil. It can also be seen from Fig. 8 that using the value of 0.5 for σ has a minimum percent of average error. Also, the results obtained from the MLP network shows high agreement with the experiment.

V. Concluding Remarks

Artificial Neural Network was used to predict the aerodynamic coefficients of an airfoil oscillating in plunge at various conditions. For this purpose, series of experimental tests have been developed for a section of a 660kw wind turbine blade equipped with 64 pressure transducers along its chord. For training the network, input data were sets of instantaneous angle of attack, reduced frequency, and amplitude of the motion for each case. Related Aerodynamic coefficients were considered for the output one. The validity of the applied methods was investigated at several cases to ensure their effectiveness to provide desired results with permissible error. Results show that with employing these trained GRNN and MLP networks the aerodynamic coefficients are predicted accurately with minimum experimental data; hence reducing the cost of tests while achieving acceptable accuracy.

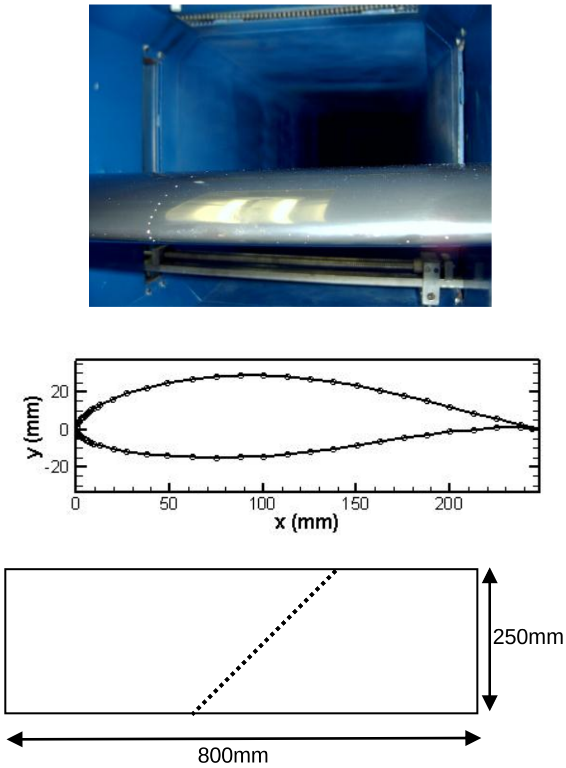
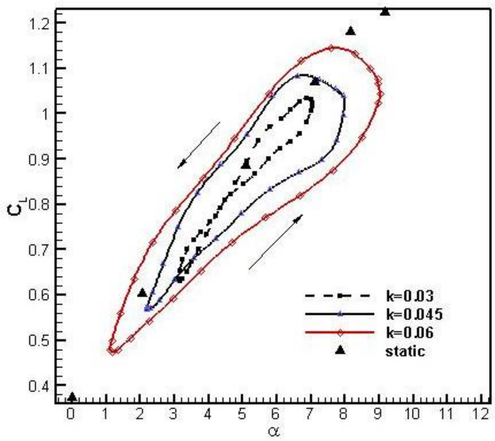
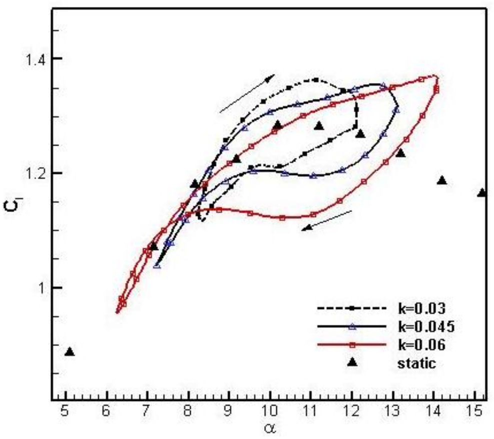


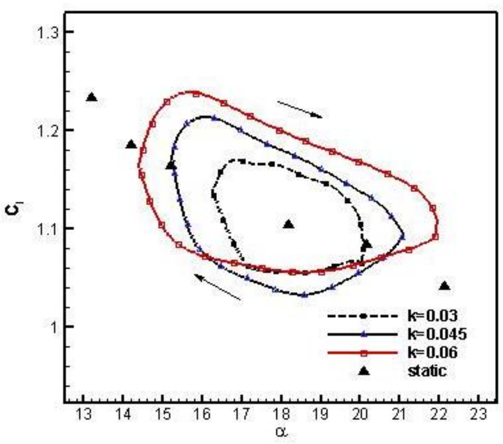
Figure 1. Airfoil model and the location of the pressure ports.



a) $\alpha_0 = 5°$

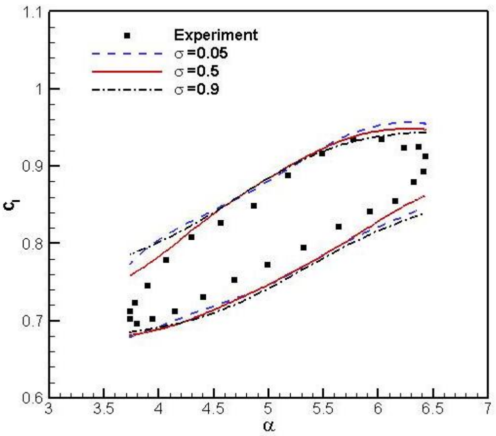


a) $\alpha_0 = 10°$

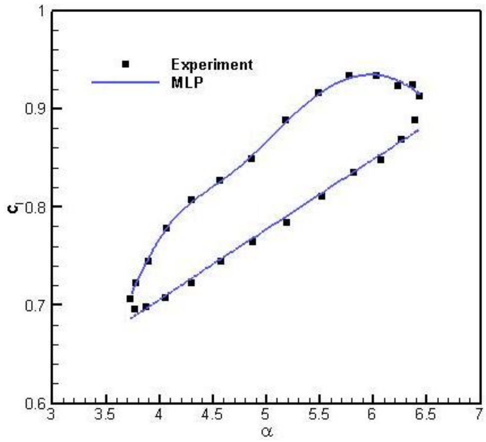


a) $\alpha_0 = 18°$

Figure 2. Variation of lift coefficient with equivalent angle of attack



a) GRNN



b) MLP network

Figure 3. Comparison between experimental and Artificial Neural Network results, $\alpha_0 = 5°$.

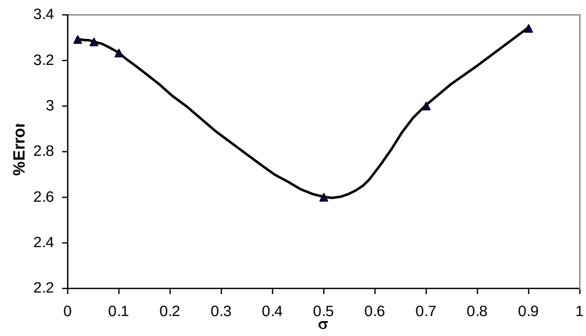


Figure 4. Variation of error with spread parameter, σ in GRNN, $\alpha_0 = 5°$.

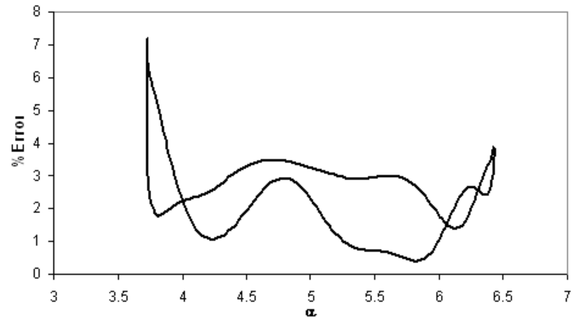


Figure 5. Variation of error with angle of attack in GRNN, σ=0.5, $\alpha_0 = 5°$.

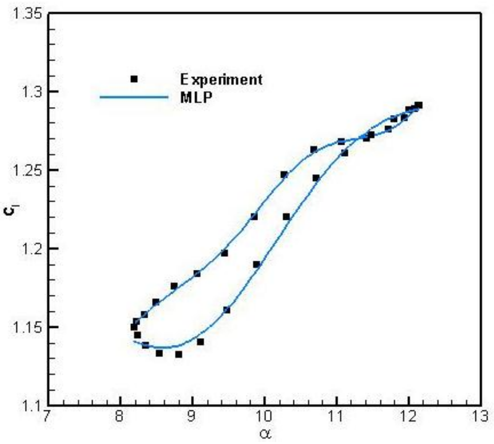
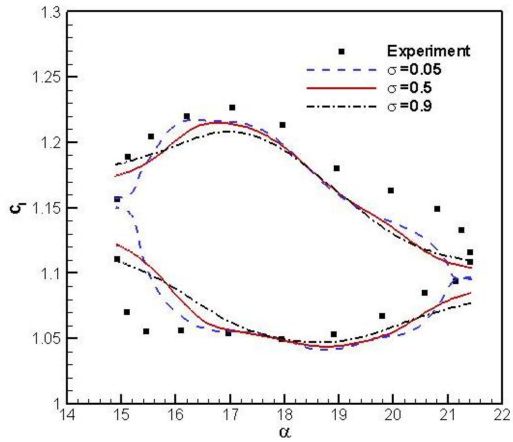
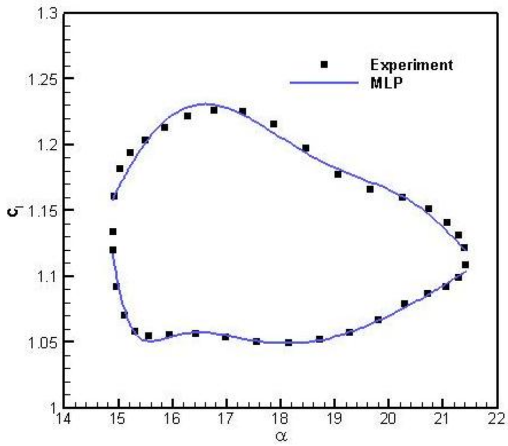


Figure 6. Comparison between experimental and MLP network results, $\alpha_0 = 10°$.



a) GRNN



b) MLP network

Figure 7. Comparison between experimental and Artificial Neural Network results, $\alpha_0 = 18°$.

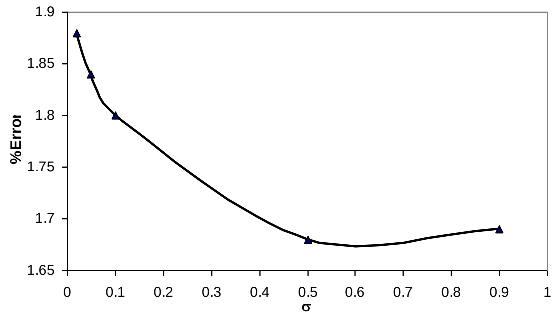


Figure 8. Variation of error with spread parameter, σ in GRNN, $\alpha_0 = 18°$.

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