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Application of Artificial Neural Network for the Prediction of Pressure Distribution of a Plunging Airfoil

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Abstract**—**Series of experimental tests were conducted on a section of a 660 kW wind turbine blade to measure the pressure distribution of this model oscillating in plunging motion. In order to minimize the amount of data required to predict aerodynamic loads of the airfoil, a General Regression Neural Network, GRNN, was trained using the measured experimental data. The network once proved to be accurate enough, was used to predict the flow behavior of the airfoil for the desired conditions.

Results showed that with using a few of the acquired data, the trained neural network was able to predict accurate results with minimal errors when compared with the corresponding measured values. Therefore with employing this trained network the aerodynamic coefficients of the plunging airfoil, are predicted accurately at different oscillation frequencies, amplitudes, and angles of attack; hence reducing the cost of tests while achieving acceptable accuracy.

Keywords**—** Airfoil, experimental, GRNN, Neural Network, Plunging.

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 aeroelastic 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 airloads and aeroelastic 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 and different mean angles of attack. 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 pressure distribution and 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 cm × 80 cm × 200 cm. The test section speed varies continuously from 10 to 100 m/sec, at Reynolds

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number of up to 5.26×10^6 per meter. The model considered in the present study has 25 cm chord and 80 cm span and is the critical section of a 660 kW 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.

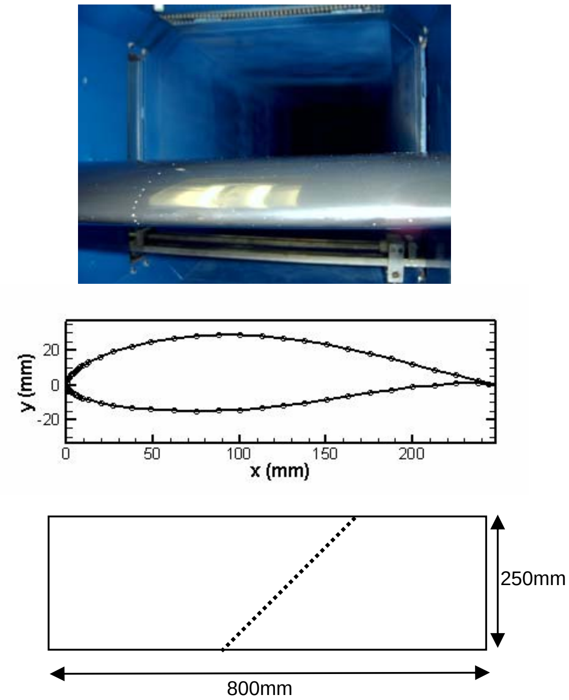


Fig. 1 Airfoil model and the location of the pressure ports

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 network used in this study is GRNN which is a three-layer network that can be used to estimate the nonlinear functions. Fast training is an outstanding characteristic of this routine, which allows engineers to deal with time variant systems [9]. Training of GRNN begins with a collection of input-output couples, and data classification can be accomplished by a proper method of clustering. After training, GRNN is ready for estimation. Spread parameter, σ, is an important parameter for training the GRNN. The performance of neural network is very sensitive to this parameter [10].

In this study the GRNN after training uses 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 pressure coefficients of the related angles of attack at some locations of the airfoil surface. 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. Furthermore, unsteady lift coefficients are calculated using predicted pressure coefficients and are compared with the corresponding values obtained from experimental pressure distribution.

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 from experiment are shown in Fig. 2 for three different mean angles of attack of 5, 10, and 18 degrees and reduced frequencies of 0.03, 0.045, and 0.06 for constant plunging amplitude of ±15 cm. An arrow gives the direction of each loop. The corresponding static values are shown for comparison. 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 downstroke lift coefficients are the same, for a specific induced angle of attack, α=4°. 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 hystersis loops. Looking at Fig. 2b, it is seen that plunging the airfoil near its static stall angle, $\alpha_{static-stall} \approx 11°$, 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 GRNN is trained using the measured experimental data to minimize the amount of data required to predict aerodynamic loads of the airfoil. For training the network, the input data are included of sets of instantaneous angle of attack, reduced frequency, and amplitude of motion for each case. Related pressure coefficients are considered for the output ones. The validity of the applied method is investigated at several cases to ensure its effectiveness to provide desired results with permissible error. Here the results of two positions of the airfoil: x/c=5% and x/c=50% of upper surface are presented for two cases of mean angles of attack of 5° and 10°.

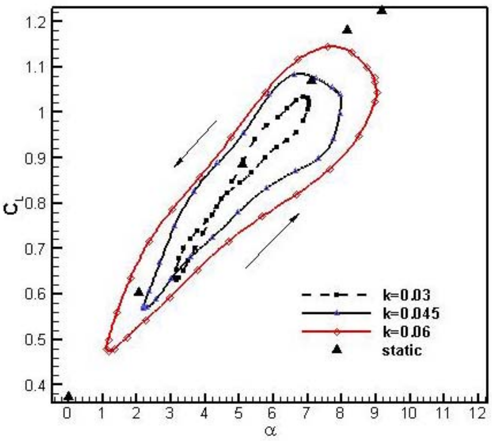
Comparison between the expected data and their predicted ones for the pressure coefficient from Artificial Neural Network at locations: x/c=5% and x/c=50% of upper surface of the airfoil are shown in Fig.'s 3 and 5, respectively. The model is set to mean angle of attack of 5 degrees and oscillated with a plunging amplitude of ±5 cm at a frequency of 2.22 Hz (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 downstroke portions of the hystersis loops. It is seen that the spread parameter has an important role in predicting the results of this network. The results for selected values of 0.002, 0.0225, 0.03 and 0.1 for the spread parameter are shown in these figures. It is seen that for the case of σ=0.0225, the prediction of the network is better than the other values. It can also be seen from Fig.'s 4 and 6 that using the value of σ=0.0225 has a minimum percent of average error. Although Fig. 4 states that the error for the case of σ=0.002 is slightly less than the case of σ=0.0225, but from Fig. 3 it is clear that the prediction of the network has some dispersions from the experimental data.

In Fig.'s 7-10, the model is set to mean angle of attack of 10 degrees, the oscillation frequency is 3.33 Hz and the amplitude of the motion is ±5 cm. For training the network, three sets of data, related to various amplitudes and frequencies, but with the same mean angle of attack are used. Various spread parameters are examined to provide desired results with permissible error. The results for σ=0.002, 0.01, 0.02 and 0.025 are shown in these figures for both cases of x/c=5% and 50% of upper surface. It is seen that for the case of σ=0.01, there is a better agreement between the result of the network and experiment. It can also be seen from Fig.'s 8 and 10 that using the value of σ=0.01 has a minimum percent of average error which is about 0.4% for the case of x/c=5% and 0.08% for the case of x/c=50%. Also, the location of the crossover point (mentioned before in Fig. 2b) is well predicted by choosing this value for the spread parameter.

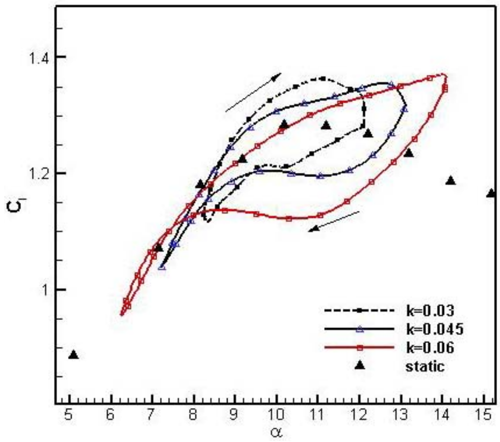
Also, lift coefficients are calculated by integrating predicted pressure coefficients obtained from all 64 pressure ports of the airfoil surface and are compared with experimental results. Fig. 11 shows the variation of the lift coefficient with equivalent angle of attack from both GRNN and experiment results for mean angle of attack of 5°. The spread parameter is set to 0.0225. It is seen that employing the trained GRNN, the lift coefficients are predicted accurately with average errors of about 1.2 % for both upstroke and down stroke motions of the airfoil. In Fig. 12, the mean angle of attack is 10° and the spread parameter is 0.01. It is clear that there is a good agreement between the predicted and experimental results with acceptable accuracy.

V. CONCLUSION

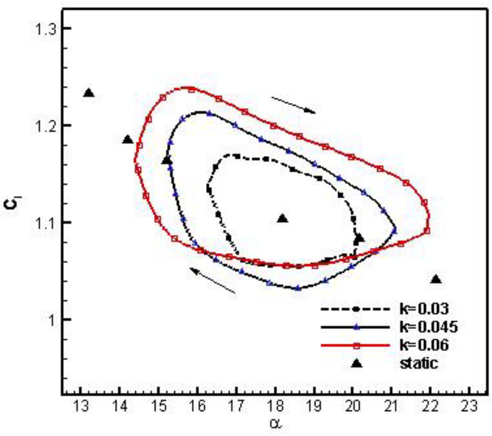
Artificial Neural Network was used to predict the aerodynamic coefficients of an airfoil oscillating in plunge at various conditions. For this purpose, series of experimental tests have been developed for a section of a 660 kW wind turbine blade equipped with 64 pressure transducers along its chord. For training the network, input data were sets of instantaneous angle of attack, reduced frequency, and amplitude of the motion for each case. Related pressure 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 showed that with employing the trained GRNN the aerodynamic coefficients are predicted accurately with minimum experimental data; hence reducing the cost of tests while achieving acceptable accuracy.



(a) $\alpha_0 = 5°$



(b) $\alpha_0 = 10°$



(c) $\alpha_0 = 18°$

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

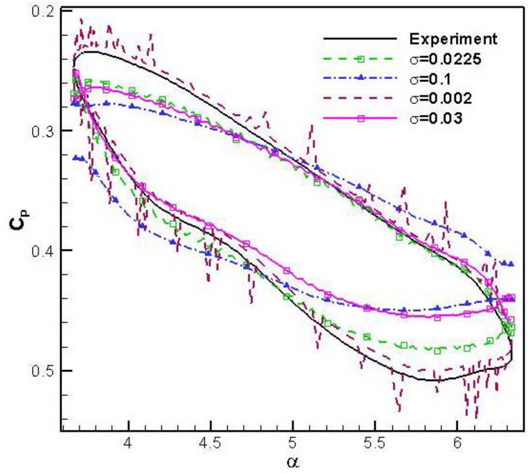


Fig. 3 Comparison between experimental and Artificial Neural Network results, x/c=5% upper surface, $\alpha_0 = 5°$.

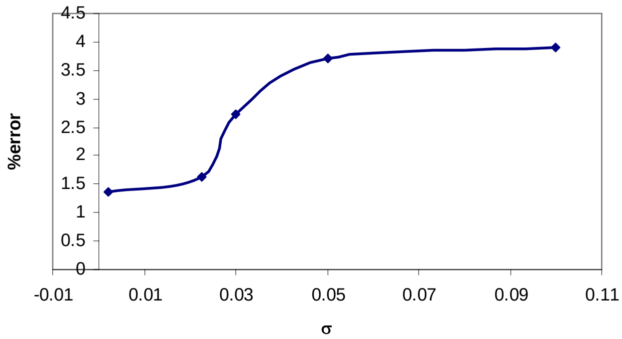


Fig. 4 Variation of error with spread parameter, x/c=5% upper surface, σ, $\alpha_0 = 5°$.

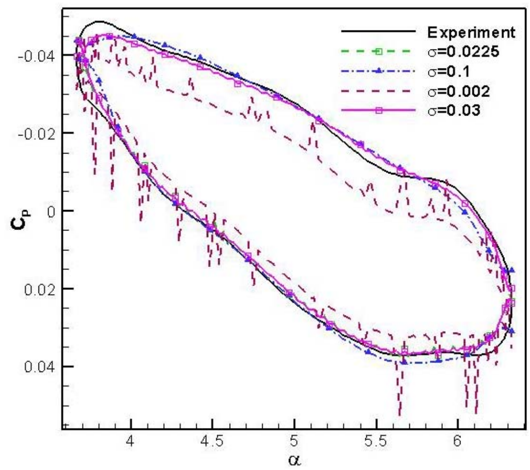


Fig. 5 Comparison between experimental and Artificial Neural Network results, x/c=50% upper surface, $\alpha_0 = 5°$.

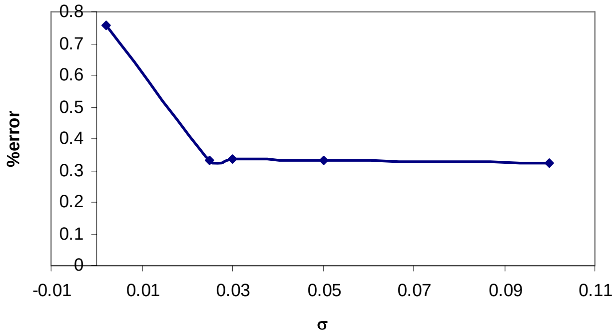


Fig. 6 Variation of error with spread parameter, x/c=50% upper surface, σ, $\alpha_0 = 5°$

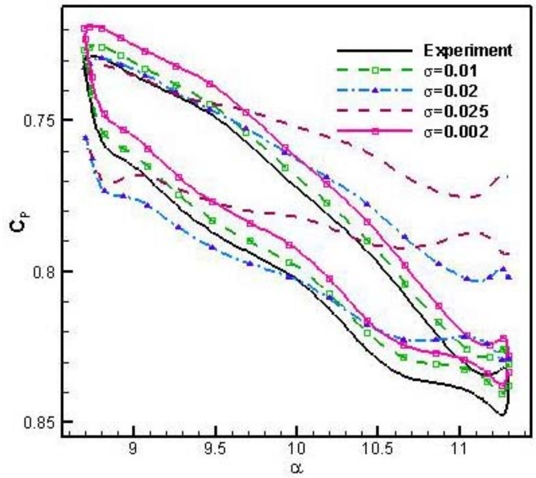


Fig. 7 Comparison between experimental and Artificial Neural Network results, x/c=5% upper surface, $\alpha_0 = 10°$

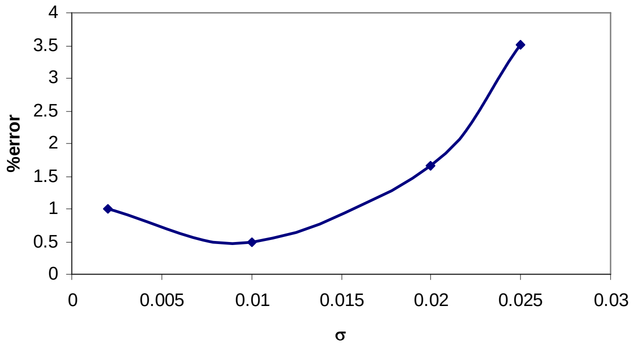


Fig. 8 Variation of error with spread parameter, x/c=5% upper surface, σ, $\alpha_0 = 10°$

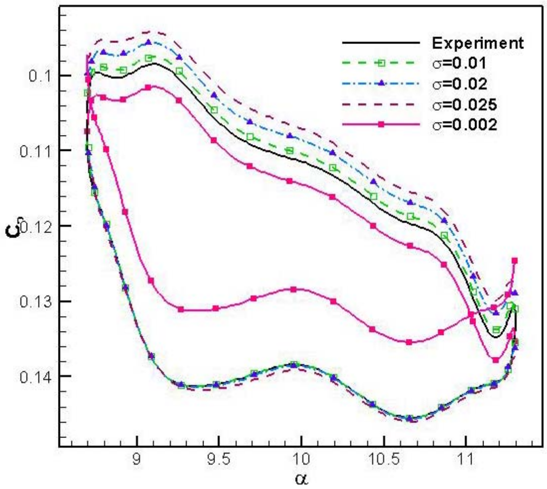


Fig. 9 Comparison between experimental and Artificial Neural Network results, x/c=50% upper surface, $\alpha_0 = 10°$

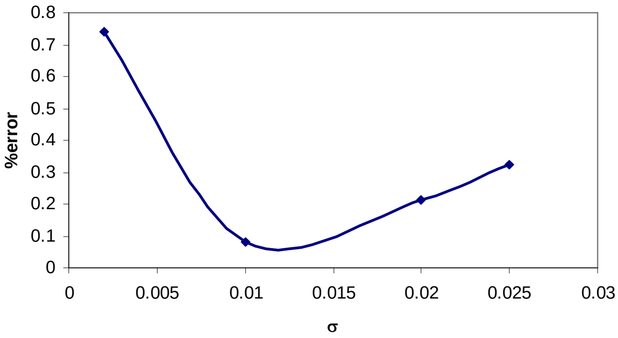


Fig. 10 Variation of error with spread parameter, x/c=50% upper surface, σ, $\alpha_0 = 10°$

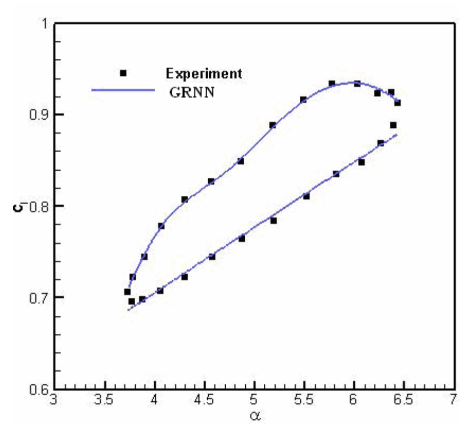


Fig. 11 Variation of lift coefficient, σ = 0.0225, $\alpha_0 = 5°$

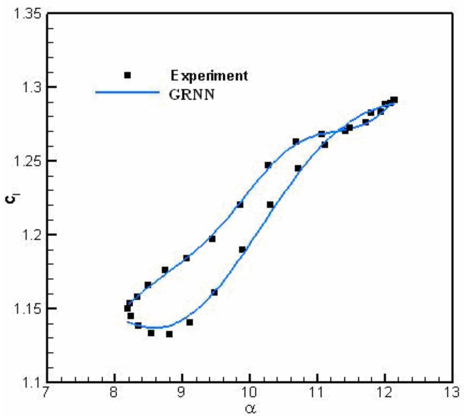


Fig. 12 Variation of lift coefficient, σ = 0.01, $\alpha_0 = 10°$

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