Neural Network Prediction of Aerodynamic Coefficients of a Pitching Wing

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Abstract. A general regression neural network (GRNN) is employed to predict the aerodynamic coefficients of an oscillating model. The results indicate that the GRNN predictions are very sensitive to the width of the probability σ. Furthermore, the sensitivity of the GRNN technique to the number of training data is investigated. It is found that as the number of samples is reduced to about 22% of the available samples, the aerodynamic coefficients are predicted with an accuracy of approximately 96%. In general, the results highlight the capability of GRNN in performing design approaches as well as optimization studies of sufficient accuracy with modest amount of data for the aerodynamic blade design in wind turbine applications.

Keywords: unsteady wing, aerodynamic coefficient, general regression neural network (GRNN).

1. Introduction

Wind turbines, renewable energy devices, are playing a very important role in the production of electricity. Even though many of the aerodynamic phenomena occurring during the operation of these devices are known, the details of flow are still poorly understood [1], and a lot of studies are being conducted to investigate these details.

Wind turbines are subjected to complicated effects such as environmental turbulence, directional and spatial variations in the wind shear, and oscillations. Moreover, the flow fields on wind turbines are characterized by significant three-dimensionality and in a large part by the unsteady dynamically stalled flows. These highly nonlinear, spatially and temporally complex flow fields make simulation of the fluid dynamics and aerodynamic loads extremely difficult [1-3]. As a result, analytical methods are not able to solve unsteady flows with sufficient accuracy. Moreover, computational solutions require large amount of processor time in spite of being potentially accurate. Experiments are also complicated, time consuming and expensive.

Among the scientific communities, the application of Artificial Neural Networks (ANNs) is growing owing to their fast, reliable, and computationally inexpensive response. Several attempts have been made to apply these techniques to systems in aerodynamics. The applicability of ANNs in predicting aerodynamic forces and reducing required training data in unsteady flows are examined by several researchers [4-7]. However, information and highly accurate prediction methods in three dimensional unsteady flows are rare and more works are needed to better understand the flow fields; hence be able to

In the present paper, ANNs are employed to reduce the number of experimental points required for constructing flow fields as well as calculation of aerodynamic coefficients for the desired model. The input data used in training the network is from an extensive experimental study over a pitching wind turbine blade tested in a subsonic wind tunnel in an unsteady flow field [8].

2. Methods

The present paper attempts to develop an accurate tool used for predicting aerodynamic coefficients of a wind turbine blade. As a first step, the lift coefficient curves are experimentally investigated using a subsonic wind tunnel, three dimensional oscillating model, and other necessary apparatus. These experimental data are then used to train a general regression neural network (GRNN) and to validate the predicted values.

2.1. GENERAL REGRESSION NEURAL NETWORK

A general regression neural network (GRNN), Specht's term [9] for kernel regression, approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. It does not require an iterative training procedure. Furthermore, it is consistent; that is, as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. The GRNN is used for estimation of continuous variables, as in standard regression techniques. It is based on a standard statistical technique called kernel regression. By definition, the regression of a dependent variable y on an independent x estimates the most probable value for y, given x and a training set. The regression method will produce the estimated value of y that minimizes the MSE. GRNN is a method for estimating the joint probability density function (pdf) of x and y, given only a training set. The pdf is derived from the data with no preconceptions about its form; hence, the system is perfectly general.

2.2. UNSTEADY SURFACE PRESSURE MEASUREMENTS

Surface pressure measurements were obtained for a harmonically pitching wing the airfoil of which belongs to a 660 kW wind turbine blade under construction in Iran. All tests were conducted in a closed circuit subsonic wind tunnel that has a test section dimension of $80 \times 80 \times 200$ cm^3.

The model had 60cm span and 25cm chord length (Fig. 1) and was bounded through its root section to the tunnel wall. Three stations were considered on the model at tip, middle, and root sections of the wing for pressure distribution study, Fig 1. At each section 25 pressure ports were used to read the surface pressure distribution, Fig 2. The real time pressure values via differential pressure transducers for various reduced frequencies were recorded and used to obtain pressure and the corresponding lift coefficients. The test matrix covers a wide range of angle o attacks at prestall, stall, and post stall conditions.

Half of the experimental data are used for training the neural network, whereas the remaining is used for validation. Inputs to the neural network are angle of attack and frequency. Different networks corresponding to different amplitudes are designed to model the effects of frequency on the aerodynamic coefficients.

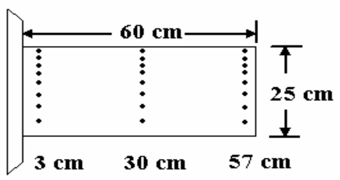

Figure 1. The upper view of the model and pressure ports

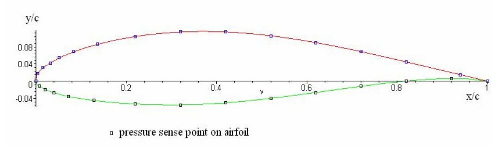

Figure 2. The schematic view of the airfoil and Pressure holes

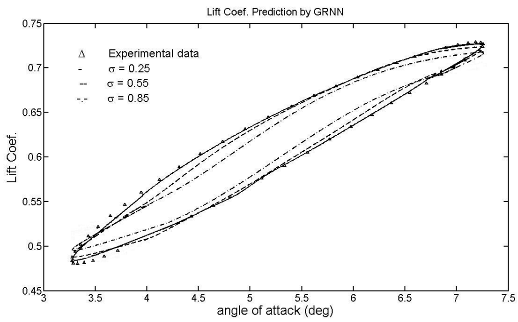

Figure 3. Effect of the width of probability σ on GRNN results

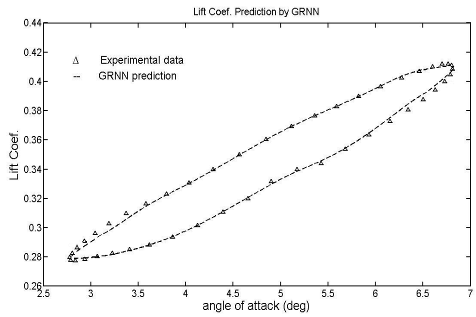

Figure 4. GRNN prediction of lift coefficient the tip section ($\alpha_0 = 5^o$, f = 1 Hz, d = 2^o, σ_{opt} = 0.25)

3. Results

As mentioned before, the main purpose of this study is to predict the lift coefficients of a three dimensional oscillatory model at the tip and middle sections. Some of the experimental data obtained from the surface pressure distribution are used to train the GRNN while the rest are used for comparison. That is, GRNN was trained using the measured data for certain oscillation frequencies. The trained network then was used to predict the variations of lift coefficient with angles of attack for various frequencies for which experimental data was available. Outputs then compared with the measured data and in this way the accuracy of the method was investigated.

As a preprocessing step, the width of probability, σ, in the GRNN needs to be determined. To this mean, an investigation is performed at all test cases examined in this paper for specific values of probability; 0.25, 0.55, and 0.85 and the result for each case is shown in Fig. 3. From this figure it is clearly seen that the predicted values change with σ noticeably and the most accurate predictions are for $\sigma_{opt} = 0.25$, where for this value of σ, the difference between the experimental and the GRNN predictions are minimal.

In Figs. 4 through 6, the lift coefficients at amplitude of 2 degrees at the tip section of the model are shown for three different frequencies. As it can be seen, the network accurately has predicted the aerodynamic coefficients at oscillation frequencies of 1 and 2.22 Hz (Figs. 4 and 6). Moreover, figure 5 illustrates network capability in predicting the lift coefficient for a frequency of f = 1.67. Note that for this frequency, f = 1.67, the network is predicting between the trained data (interpolation) and as seen from this figure, the difference between measured and predicted data are permissible.

Figures 7-10 show variations of the lift coefficient with the angle of attack at the middle section of the model for the same amplitude of the motion, 2 degrees. While Figs. 7 and 10 show the experimental and predicted results at the frequencies used for training the network, Figs. 8 and 9 demonstrate the network ability in predicting the lift coefficient at different reduced frequencies with a very acceptable accuracy.

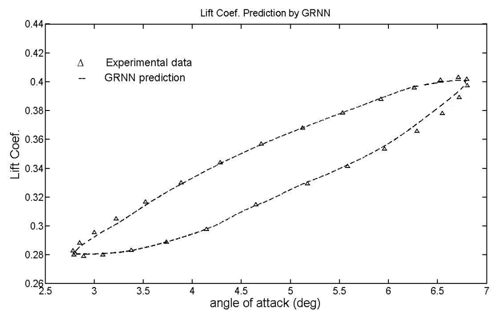

Figure 5. Tip section, f = 1.67 Hz, d = 2^o

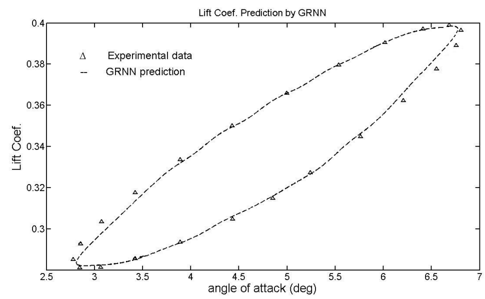

Figure 6. Tip section, f = 2.22 Hz, d = 2^o

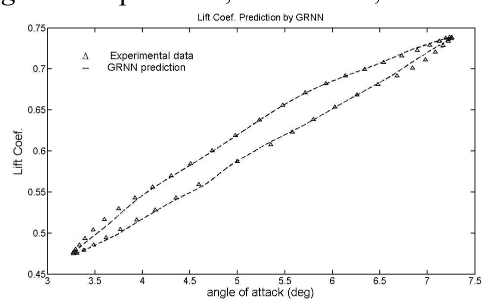

Figure 7. Middle section, f = 1 Hz, d = 2^o

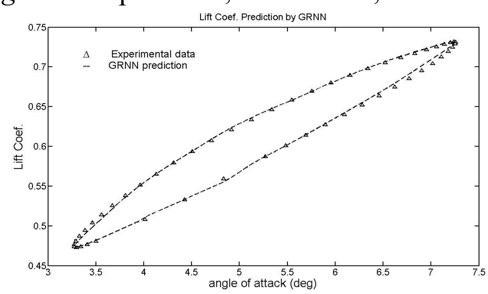

Figure 8. Middle section, f = 1.67 Hz, d = 2^o

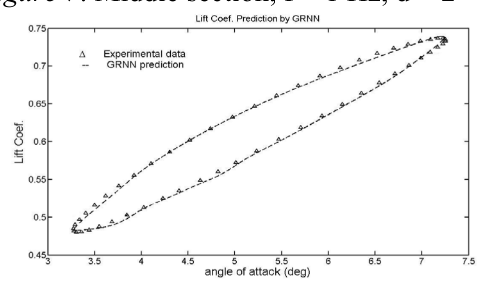

Figure 9. Middle section, f = 1.87 Hz, d = 2^o

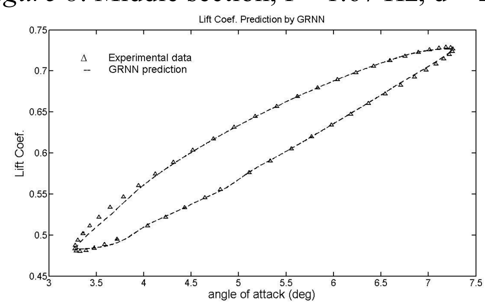

Figure 10. Middle section, f = 2.22 Hz, d = 2^o

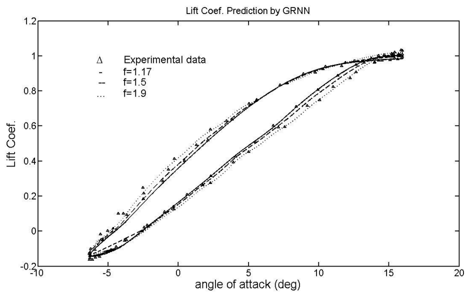

Figure 11. GRNN prediction of the lift coefficient for various frequencies (σ_{opt}= 0.25)

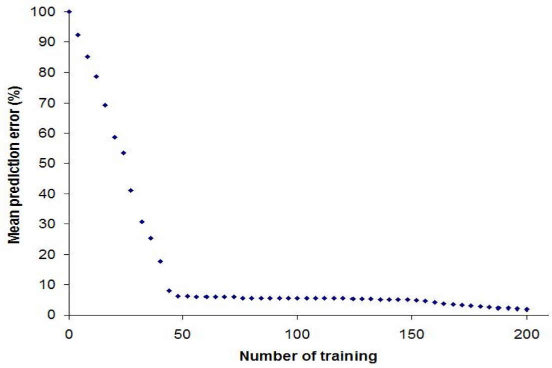

Figure 12. Mean prediction error for different number of training samples,

The lift coefficient predicted by the GRNN for the middle section of the model is shown in Fig. 11. As seen from this figure, there exists a figure eight shape in both the experimental and measured data which is an indication of the separation phenomena. It is seen by this figure that the network has been able to predict this cross over point accurately for all oscillation frequencies examined here. By using these predicted values, the lift coefficients at another oscillation frequency, f = 1.5, is predicted by the network and is seen to be in a very good agreement with the experimental data set, Fig. 11. In addition, the decreasing trend of the lift coefficient slope is predicted satisfactorily.

Figure 12 shows the mean prediction error of the GRNN at $\alpha_0 = 5^o$, f = 1.17 Hz, d = 11^o, for the middle section, as a function of a randomly selected number of training points. As it can be seen by inspection, the error approaches a steady value at about 45 training points which is 22% of the available samples and the accuracy of approximately 94% (mean error of 6%) has been obtained. This figure clearly shows that once the network has been trained carefully, it can predict the data with sufficient accuracy and reduces the experimental tests significantly.

4. Conclusion

Unsteady surface pressure distributions are obtained at four different frequencies, and two oscillation amplitudes from 2 to 11 deg. Using this data, the neural network models are developed.

The results indicate that aerodynamic coefficients at different frequencies are accurately predicted within 4% of the experimental data. Consistent results are obtained both for the training data as well as generalization to other frequencies. Moreover, an investigation is made on the sensitivity of the neural network on the number of training samples. It is observed that as one reduces the number of samples to about 22% of the available experimental data, the aerodynamic coefficients can still be predicted with an accuracy of 94%.

References

1. Leishman, J. G. and Martin, G. L., Challenges in Modeling the Unsteady Aerodynamic of Wind Turbines, In *21st ASME Wind Energy Symposium and the 40th AIAA Aerospace Sciences Meeting*, Reno, NV, USA (2002) 2002-0037.
2. Hansen, A., P. and Butterfield, C. P., Aerodynamics of Horizontal Axis Wind Turbine, In *Annual Reviews Fluid Mechanics* (1993) 115-149.
3. Huyer, S., A., Simms, D., and Robinson, M., C., Unsteady Aerodynamics Associated with a Horizontal Axis Wind Turbine. *J. AIAA*. **34** (1996) 1410-1419.
4. Faller, W., A Unified RNN Blade Flow Model Rotating Blade and Yawed Turbine Conditions, In *44th Aerospace Sciences and Exhibit*, Reno NV, USA (2006) 1-17.
5. Faller, W., Real-Time Model of Three Dimensional Dynamic Reattachment Using Neural Networks, *J. Aircraft*. **32** (1995) 1177-1182,
6. Norgaard, M., Jorgensen, C. C., and Ross, J. C., "Neural Network Prediction of New Aircraft Design Coefficients," NASA TM 112197, 1997.
7. Soltani, M. R., Sadati, N., and Davari, A. R., Neural Network: A New Prediction Tool for Estimating the Aerodynamic Behavior of a Pitching Delta Wing, AIAA Paper 2003-3793.
8. Soltani, M.R. and Amiralaei M.R., Effects of Reduced Frequency on Lift Coefficients of A Harmonically Pitching Wing, In *The 6th Iranian Aerospace Society Conference*, Tehran, Iran. (2007) 125-130.
9. Specht, D. F., A General Regression Neural Network, *IEEE Trans. Neural Networks*. **2** (1991) 568–576.