INTERNATIONAL CENTER FOR NUMERICAL METHODS IN ENGINEERING

A Neural Networks Approach to Aerofoil Noise Prediction

K. Lau, R. López, E. Oñate

Publication CIMNE Nº-335, 2009

A Neural Networks Approach to Aerofoil Noise Prediction

K. Lau
R. López
E. Oñate

Publication CIMNE Nº-335, 2009

International Center for Numerical Methods in Engineering
Gran Capitán s/n, 08034 Barcelona, Spain

A Neural Networks Approach to Aerofoil Noise Prediction

Kevin Lau *, Roberto Lopez, Eugenio Oñate

International Center for Numerical Methods in Engineering, Technical University of Catalonia, 08034 Barcelona, Spain

Abstract

A neural network noise prediction model for a turbulent boundary layer noise mechanism has been created using a feed forward multilayer perceptron and a noise spectrum database collected from a family of NACA 0012 aerofoils. The results of the neural network model were compared against the Brooks model and it was found that the quality of the prediction was improved over the entire range of the data. The model was also validated against experimental data not utilised the training of the neural, with positive results.

Key words: aerofoil, noise prediction, neural network, semi-empirical model

1 Introduction

The noise generated by an aircraft is an efficiency and environmental issue for the aerospace industry. NASA have issued a mandate to reduce the external noise generated by the whole airframe of an aircraft by 10 decibels (dB) in the near term future [13]. A component of the total airframe noise is the self-noise of the aerofoil itself; this is defined as the noise generated when the aerofoil passes through smooth non-turbulent inflow conditions. The noise is generated through an interaction of the aerofoil with its own boundary layer and/or the near wake region.

* Corresponding author.
Email addresses: kevin.lau@imperial.ac.uk (Kevin Lau), rlopez@cimne.upc.edu (Roberto Lopez), onate@cimne.upc.edu (Eugenio Oñate).

Preprint submitted to Elsevier 2 October 2006

Journal of Aerospace Science & Tech.

There have been various modeling attempts to predict the noise of an aerofoil. Howe [11] reviewed the various methodologies and grouped the different approaches into three groups:

- Theories based upon the Lighthill acoustic analogy [12],
- Theories based on the solution of special problems approximated by the linearised hydrodynamics equations [1] [2] [8],
- Semi-empirical models [4].

An example of a semi-empirical model is the model of Brooks, Marcolini and Pope [4], referred to here as the *Brooks model.* This model was formulated from an extensive set of acoustic wind tunnel tests, upon several different chord length NACA 0012 aerofoil sections. By using a scaling rule to scale the noise generated by the aerofoil (see Section 4.1) a noise prediction model dependent on the frequency of the noise, the angle of attack,the freestream velocity and the geometric parameters of the aerofoil was created. More details on the experimental procedures and the modeling methodology for the Brooks model are contained within [4]. Formulated in 1989 the Brooks model is still utilised for noise prediction in wind turbine designs [1].

2 Data Modeling

Both the Brooks model and the neural network model in this paper are examples of data modelling, or *function regression.* The aim of function regression is to model the conditional distribution of the output variables, conditioned upon the input variables. Using an input-target data set, a function relating the input variables to the output variables can be approximated [3].

Determining the correct function complexity is often complicated by the presence of random noise in the input-target data set. The aim is to determine the most appropriate model complexity which represent the trends within the data, whilst ignoring the specifics of the noise. If the model complexity is too simple, then the data is *under-fitted* and the trends in the data are ignored; conversely if too complex then the data is *over-fitted* and the model cannot differentiate between the trends in the data and the noise. The choice of model complexity is a design variable and is discussed in Section 4.2.

[1] NREL Airfoil Noise: http://wind.nrel.gov/designcodes/simulators/NAFNoise/

3 Neural Networks

A neural network is a collection of data processing units, termed neurons, interconnected to each other. Each neuron adopts a different state depending upon the inputs of the network. Output neurons then interpret these states, yielding the output of the network. Neural networks can be adapted to a multitude of different tasks by adapting the free parameters of the network until the correct output is achieved. This flexibility allows the neural network to model the functional dependency of any problem. The complexity of this modeling ability is determined by the number of neurons utilised within the neural network.

Neural networks are capable of representing any function in any dimension and up to any desired degree of accurac They have been described as universal approximation functions [10], making neural networks an ideal tool for function regression. In this paper a noise prediction model has been created by performing function regression using a neural network with an input data set of aerofoil parameters and a target output of the aerofoil noise emissions. Artificial neural networks have also been successfully applied to a range of aeronautical issues in fault diagnostics, modeling and simulation and control systems [6].

The artificial neural network application used in this paper is the open source neural networks C++ library Flood [2]. The artificial neural network type utilised by Flood is known as the *multilayer perceptron*. The four components of this artificial neural network are described in the following sections.

3.1 Neuron Model

The neuron model used by Flood is the perceptron. This forms the characteristic component of the mulitlayer perceptron. A perceptron is defined by 3 different parameters: the free parameters of the perceptron, a combination function and an activation/transfer function [9] and [14].

The free parameters of each perceptron consists of a bias value b, and a vector of synaptic weights $\mathbf{w}^T = [w_1, \ldots, w_n]$, where n corresponds to the number of input nodes. The combination function h within the perceptron determines the dot product of the input signal vector, $\mathbf{x} = [x_1, \ldots, x_n]^T$, with the synaptic weight vector plus the bias value.

The output of the combination function is termed u, and is passed to the

[2] www.CIMNE.com/flood

activation function. The activation function $g(u)$ yields the output signal of the perceptron, y. There are a variety of activation functions that can be used [5], but the most frequently used activation functions are the linear and sigmoid functions [9]. Equation 1 defines the output of the perceptron in terms inputs and the free parameters.

$$y(\mathbf{x}; b, \mathbf{w}) = g\left(b + \sum_{i=1}^{n} w_i x_i\right) \tag{1}$$

3.2 Network Architecture

The manner in which the neurons within the network are connected together and arranged is described as the network architecture. The characteristic network architecture used in the multilayer perceptron is the feed forward architecture [14]. The feed-forward network architecture typically consists of an input layer of sensorial nodes, one or more layers of hidden neurons and an output layer of neurons. Information passes from the input layer to the output layer via the hidden layers.

The output at some node y_k, is given as a combination of the outputs of all the individual perceptrons in the hidden layer. This is expressed as shown in Equation 2.

$$y_k(\mathbf{x}; \underline{\alpha}) = g^{(2)}\left(b_k^{(2)} + \sum_{j=1}^{h_1} w_{kj}^{(2)} \cdot g^{(1)}\left(b_j^{(1)} + \sum_{i=1}^{n} w_j^{(1)} x_i\right)\right) \tag{2}$$

The index k extends over the outputs, $k = 1, \ldots, N_{outputs}$. The index j extends over the hidden layer, $j = 1, \ldots, h_1$. The superscripts (1) and (2) refer to the hidden and output layer, i.e. the function $g^{(1)}$ refers to the activation function of a perceptron in the hidden layer and the function $g^{(2)}$ to a output perceptron.

3.2.1 Objective Functional

The suitability of the neural network model is evaluated using an objective functional, which measures the quality of the output against the target data. For this application the objective functional used is the *mean squared error* (MSE). The MSE is calculated as the square of the difference between the known output ($y_{measured}$)and predicted output of the neural network ($y_{predicted}$), summed over all of the samples and averaged using the total number of samples.

Defined in terms of the parameters of the multilayer perceptron, the MSE is given as shown in Equation 3. The index q extends over Q samples of the input-target data set, and the index k over the number of outputs of the system. The term t_k is the target output of the system; zero error is achieved when the output of the system y_k is equal to t_k.

$$\mathrm{MSE}[\mathbf{y}(\mathbf{x};\underline{\alpha})] = \frac{1}{Q}\sum_{q=1}^{Q}\left(\sum_{k=1}^{m}\left[y_k(\mathbf{x}^{(q)};\underline{\alpha}) - t_k^{(q)}\right]^2\right) \tag{3}$$

3.3 Training Algorithm

The magnitude of the error between the neural network output and the target data is reduced by optimising the free parameters of the multilayer perceptron ($\underline{\alpha}$) using a training algorithm.

The training algorithm used in this application was the conjugate gradient method [15]. This is a first order algorithm, as it uses both the objective function and its gradient vector to optimise the free parameters in the network.

4 Noise Prediction Neural Networks

A neural network has been created to model the noise generated by *turbulent boundary layer* noise mechanism. This noise is generated at high Reynolds number flow conditions, where the boundary layer upon the aerofoil is turbulent; noise occurs from the boundary layer itself and when the turbulence passes over the trailing edge of the aerofoil and mixes with the free-stream flow.

4.1 Input-Target Data

The input-target data set was created from a noise database taken by digitising the appropriate figures from [4]. The database contains 1503 entries and consists of the following variables:

Database Variables: frequency (Hz), angle of attack ($^\circ$), chord length (m), span (m), freestream velocity (ms^{-1}), suction side displacement thickness [3]

[3] The suction side displacement thickness was determined using an expression derived from boundary layer experimental data from [4].

(m), retarded observer distance (m), observer position angles [θ and ϕ] $(^\circ)$ and sound pressure level[4] (dB)

The input-target data set was created by using a scaling rule to reduce this set of 9 variables to 5. Following the methodology of the Brooks model the 9 variables are scaled using a pressure noise scaling observation from Ffowcs-Williams and Hall [7], reducing the 9 input variables to 5. The final 5 input variables and single target variable are:

Input Variables: frequency (Hz), angle of attack $(^\circ)$, chord length (m), freestream velocity (ms^{-1}) and suction side displacement thickness (m)
Output/Target Variable: Scaled sound pressure level (dB)

The scaled sound pressure level is given by Equation 4. The terms M, L, δ_s^* and r_e are the Mach number, aerofoil span, suction side displacement thickness and the retarded observer position respectively.

$$\text{Scaled SPL}_{1/3} = \text{SPL}_{1/3} - 10\log\left(M^5\frac{\delta_s^* L}{r_e^2}\right)\overline{D} \tag{4}$$

For all of the data sampled the directivity factor, $\overline{D}$, is equal to unity. This corresponds to an observer position normal to the surface of the trailing edge.

4.2 Training Results

To determine the correct functional complexity for our neural network model, several different neural networks with differing complexity were created. These were all trained with the same training data set. The model complexity was then assessed using a separate validation data set; using this data set it can be seen if the current model is over or under-fitting the data.

The validation data set consists of all the data from the 10.16 cm chord length aerofoil. This set contains 263 samples, representing approximately 18% of the full database. The training data set consists of the remaining data. The neural networks were trained with the training data set with the following stopping criteria:

- Evaluation Goal: 0.001,
- Gradient Norm Goal: 0.0,
- Maximum Training Time: 1000000 seconds,
- Number of Training Epochs: 15000.

[4] Note that the sound pressure level is sampled in the 1/3 octave spectrum

After this training the error (MSE) was then evaluated using the validation data set. The training and validation data can be seen in Table 1. From the training and validation MSE for neural networks with 5, 10 and 15 neurons in the hidden layer it can be seen that with 5 neurons in the hidden layer there is under-fitting, and with 15 there is over-fitting for the data.

Table 1
- Training and validation error.

Number of Neurons	5	10	15
Training Error	6.722	3.731	2.500
Validation Error	15.093	12.094	19.866

5 Noise Prediction Results

After determining the optimal network architecture as 5:10:1, this multilayer perceptron was then trained for a further 5000 epochs using all of the available data. Figure 1 shows the noise prediction of the neural network model against experimental data and the Brooks model. It can be seen that the Brooks model over and under-predicts the SPL at both low and high frequency values, whereas the neural network prediction closely follows the experimental data.

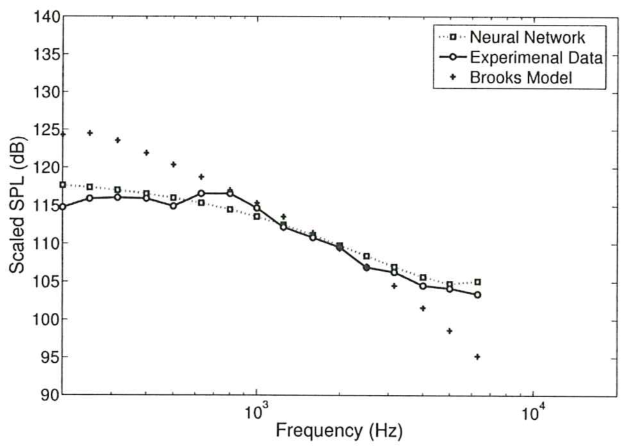

Fig. 1. Neural network prediction against experimental data and Brooks model prediction for a 15.24 cm chord length aerofoil at $\alpha = 12.6°$ and freestream velocity of 39.6ms^{-1}

The accuracy of the Brooks model and the fully trained neural network over all of the experimental configurations is displayed in Figures 2 and 3 respectively. The broken line shown in both plots represents the optimal model, in which the prediction matches the experimental data. It can be seen that the

Brooks model predicts substantially lower values of the SPL at low SPL values, showing that the Brooks model is under-fitting the data. Compare this to the neural network model which provides a better fit across all of the equipment configurations.

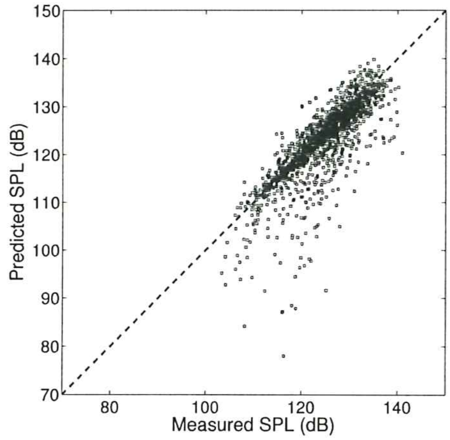

Fig. 2. Regression plot for the Brooks model; correlation coefficients $R^2 = 0.654$

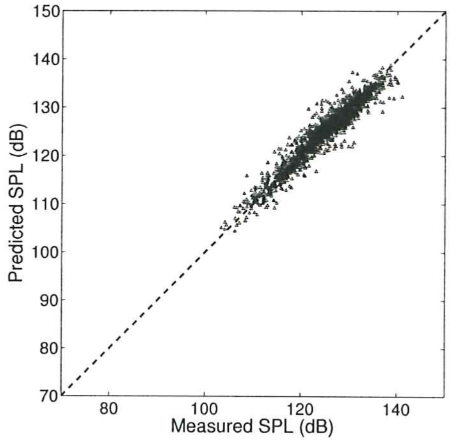

Fig. 3. Regression plot for the neural network model; correlation coefficients $R^2 = 0.917$

6 Additional Experimental Data

The Brooks model was validated using data from addition experiments on a NACA 0012 aerofoil [16]. Similarily this experimental data can also be used to test the neural network model. The aerofoil used in these experiments has the same profile but with a chord length of 0.229 m and a span of 0.533 m. The experiments were also conducted at a different observer distance (r_e=2.81 m) and over a different range of freestream velocities; but the observer position remains the same as before. The prediction of a single experiment using

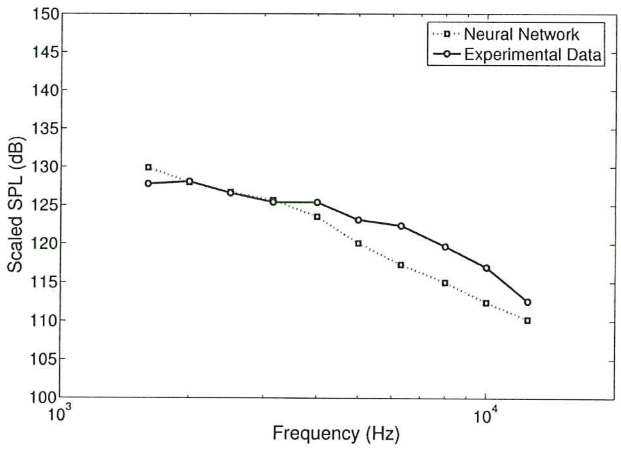

Fig. 4. Noise prediction results of a 22.9 cm chord length aerofoil at $\alpha = 3.9°$ and a freestream velocity of $61.3ms^{-1}$

the neural network model is shown in Figure 4. The suction side displacement thickness inputed into the neural network model was evaluated using the boundary layer expressions determined in [4] for an untripped boundary layer, corresponding to the experimental conditions. It can be seen that at the lower frequency values the neural network model closely follows the experimental data. At the high frequencies the prediction is lower than the experimental values, but still follows the spectral shape of the noise.

7 Conclusions and Future Work

In this paper it has been shown that neural networks can be successfully applied to the problem of aerofoil noise prediction. The noise output of an aerofoil has been parameterised using a noise scaling rule and the geometric parameters of the aerofoil. After determining the optimal neural network complexity, the prediction quality of the neural network has been compared against the existing Brooks model. Upon reviewing the prediction quality of all the experimental configurations tested, it was shown that the neural network model provided better results across the entire range. The prediction quality of the neural network was also verified upon data not included in training the neural network, with positive results shown.

It is possible to extend the work shown here to different noise mechanisms not covered in this paper. Also contained within the Brooks paper is data from a laminar boundary layer noise mechanism and the associated semi-empirical model. This model also exhibits regions of under-fitting and can be further improved upon.

References

[1] R.K. Amiet, Noise due to a turbulent flow past a trailing edge, Journal of Sound and Vibration 47(3), pp. 387-393, 1976

[2] R.K. Amiet, Effect of the incident surface pressure field on noise due to a turbulent flow past a trailing edge, Journal of Sound and Vibration 57(2), pp. 305-306, 1978

[3] C. Bishop, Neural Networks for Pattern Recognition, Oxford University Press, 1995.

[4] T.F. Brooks, D.S. Pope, A.M. Marcolini, Airfoil Self-Noise and Prediction, NASA RP-1218, July 1989

[5] Demuth, Beale, Neural Network Toolbox For Use With MATLAB. Users Guide, The Mathworks, 2002.

[6] W.E. Failer,S.J. Schrec,Neural Networks: Applications and Opportunities in Aeronautics, Prog. Aerospace Sci. Vol. 32, pp. 433-456, 1996 +

[7] J.E. Ffowcs Williams, L.H. Hall, Aerodynamic sound generation by turbulent flow in the vicinity of a scattering half plane, Journal of Fluid Mechanics 40, pp. 657-670, 1970

[8] M.E. Goldstein, Scattering and distortion of the unsteady motion on transversely sheared mean flows, Journal of Fluid Mechanics 91(4), pp. 601-632, 1979

[9] S. Haykin, Neural Networks: A Comprehensive Foundation,Prentice Hall, 1994

[10] K. Hornik, M. Stinchcombe, H. White, Multilayer Feedforward Networks are Universal Approximiators, Neural Networks, 2(5): 359-366, 1989

[11] M.S. Howe, A review of the theory of trailing edge noise, Journal of Sound and Vibration 61, pp. 437-465, 1978

[12] M.J. Lighthill, On sound generated aerodynamically: I General Theory, Proceedings of the Royal Society of London A 211, pp. 564-587, 1952

[13] D.P. Lockard, G.M. Lilley, The Airframe Noise Reduction Challenge, NASA/TM-2004-213013, 2004

[14] P. Orponen, J. Sima, General Purpose Computation with Neural Network. A Survey of Complexity Theoretic Results, Neural Computation, 15:2727-2778, 2003

[15] W.H. Press, S.A. Teukolsky, W.T. Vetterling, B.P. Flannery, Numerical Recipes in C++: The Art of Scientific Computing, Cambridge University Press, 2002.

[16] R.H. Schlinker, Airfoil Trailing Edge Noise Measurement With a Directional Mircophone, AIAA Paper 77-1269, Oct. 1977