A Neural Net Based Prediction of Sound Pressure Level for the Design of the Aerofoil

Palash Pal[1], Rituparna Datta[2], Deepak Rajbansi[3], and Aviv Segev[2]

[1] University Institute of Technology,
Burdwan University, India
pal.palash.ml.research@gmail.com
[2] Department of Computer Science,
University of South Alabama, Alabama, USA
{rdatta,segev}@southalabama.edu
[3] Design and Validation,
QuEST Global Engineering Services Private Limited, India
deepak.rajbansi@quest-global.com

Abstract. Aerofoil self-noise can affect the performance of the overall system. One of the main goals of aircraft design is to create an aerofoil with minimum weight, cost, and self-noise, satisfying all design requirements from the physical and the functional requirements. Aerofoil self-noise refers to the noise produced by the interaction between an aerofoil and its boundary layer. This paper describes how the prediction of the self-noise of an aerofoil at the early stage of the design phase can help select the best design of the aerofoil, which in turn reduces the lead time as the design process becomes more robust with respect to cost effectiveness. In the present work, the prediction of the self-noise of the aerofoil is addressed using Neural Networks (NN). Different architectures are used along with various proportions of training and testing to select the best architecture and best training-testing ratio. The results from NN is compared with linear, quadratic, and cubic polynomial regression. Thereafter, Principal Component Analysis (PCA) is integrated with NN for further improvement of prediction results. Our experimental results indicate that neural networks outperform regression. Moreover, PCA integrated with NN outperforms even the best neural network result.

Keywords: Neural Network · Back Propagation · Design of Aerofoil · Principal Component Analysis (PCA) · Regression.

1 Introduction

Aerofoil is the cross-sectional shape of a wing, blade, or sail [6]. An aerofoil shaped body moving through fluid produces an aerodynamic force [18, 9]. The component of this force perpendicular to the direction of motion is called lift. The component parallel to the direction of motion is called drag [19, 13, 15].

Aerofoils are used in aircraft as wings to produce lift or as propeller blades to produce thrust. While designing aircraft, design requirements for wings or propeller blades are fixed initially. Many parameters are taken into consideration [10, 4]. In case of the design of the wing, parameters considered are lift, drag, Critical Mach Number, angle of attack, coefficient of lift, etc. For the design of the blade parameters considered are lift, drag, pressure difference, flow rate, power generated, efficiency, angle of attack, etc. After freezing the design requirements, we need to choose suitable aerofoils that fulfil all the design requirements. Some research on aerofoil design optimisation is available in [7, 12]. Self-noise is the noise produced by one's own body. Self-noise of an aerofoil is generated by its boundary layer turbulence interacting with the trailing edge of the blades or wings. Aerofoil self-noise reduces blade efficiency and increases flutter in case of wings, thus affecting system performance and integrity [3, 17]. It is important to predict aerofoil self-noise before finalizing the design of wings or blades to prevent any unwanted overall behaviour of the system as a whole. Another study by Vathylakis et al. [3] performed a study to determine different variables which affect the self-noise reduction of an aerofoil. Chong et al. [17] performed an experimental study to reduce aerofoil self-noise.

There is no standard method available to predict aerofoil self-noise as the relationship between the input parameters and the output self-noise is random in nature. In our present experiment, an effort is made to model input parameters against output using different machine learning methods. We applied linear, quadratic, and cubic regression; neural network model [2, 16], and neural network with PCA [5, 8] to predict aerofoil self-noise.

The organisation of the rest of the present paper is as follows. Section 2 discusses the description of the self-noise dataset, provides the details of the method, and the simulation results. The future scope along with the conclusion is in Section 3.

2 Proposed method and simulation results

2.1 Self-noise dataset description

An existing open source dataset [1] is used for the present study to predict the self-noise of the aerofoil where the output is sound pressure level in decibel with five inputs. There are millions of aerofoils available which are pre-designed. Among them, more than one design may satisfy specific design requirements. Our aim is to select the most suitable aerofoil from available designs which satisfies all the design requirements and produces minimum noise (scaled sound pressure level). There is no standard mathematical formulation to determine the noise level of an aerofoil from given input data. We used Neural Network to achieve that goal. Some earlier studies that used the same dataset can be found in [11, 14]. Our input parameters are:

1. Frequency in Hertz
2. Angle of attack in degree
3. Chord length in meter
4. Free stream velocity in meter per second
5. Suction side displacement thickness in meter

Our output is scaled sound pressure level in decibels. In this experiment, our effort is to predict aerofoil noise to select the aerofoil with minimum noise that satisfies all the design requirements.

2.2 Proposed method

The neural network model is suitable when there is a nonlinear and random relationship between input and output variables. From the scatterplot matrix in Fig. 1, it is clear that different input parameters in our present experiment have a nonlinear and random relationship to the output. So, we used a neural network to predict the output against input combinations. The prediction problem is solved using multilayer feed forward back propagation network. The proposed Neural Network (NN) is considered to have five inputs (frequency in Hertz, angle of attack in degree, chord length in meter, free stream velocity in meter per second, suction side displacement thickness in meter).

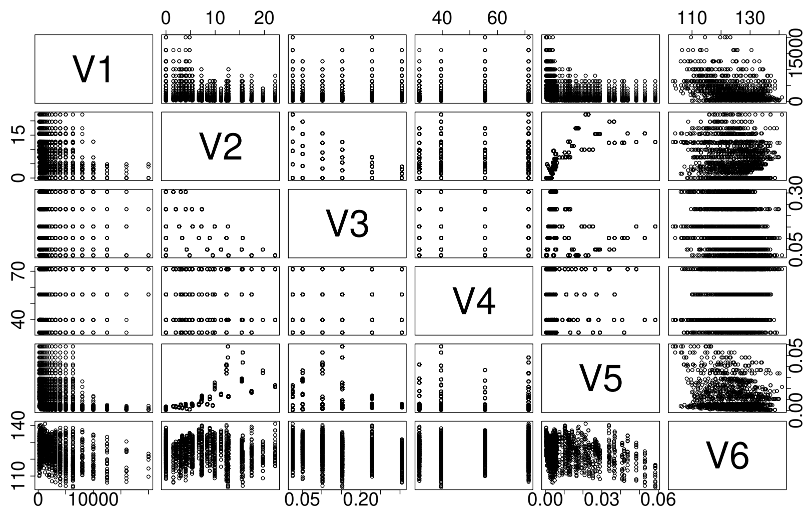

Fig. 1. Scatter plot matrix of input and output variables for visual representation.

Regression analysis is suitable to model the relationship between independent variables and dependent variables when the dependent variable is continuous in nature. In our present experiment, the dependent variable is aerofoil self-noise, which is a continuous variable in nature. So, we applied regression to model the relationship between the input and output parameters. Principal component analysis is used to transform input variables into a set of linearly uncorrelated variables. It is also a process of dimensionality reduction where less important components can be ignored while modelling the principal components against the output. In our experiment, we ignored the last component as its proportion of variance is negligible.

2.3 Simulation results

In this section we explain the simulation results. Fig. 1 presents a scatter plot matrix between five input variables with the output variable.

Table 1. Different NN architectures, regressions, and Principle Component Analysis (PCA) with NN in terms of MSE for sound pressure level prediction for aerofoil design

Training – Testing	Method	Architecture	Scaled MSE	Unscaled MSE
60% - 40 %	Neural Network	5 — 3 — 1	0.0073	12.8172
		5 — 3 — 2 — 1	0.0097	13.7662
		5 — 4 — 3 — 2 — 1	0.0032	**5.2197**
		5 — 5 — 3 — 2 — 1	0.0043	6.4114
		5 — 4 — 4 — 3 — 2 — 1	0.0042	6.2937
	Regression	Linear		25.61517
		Quadratic		21.39708
		Cubic		18.93659
	PCA with NN	4 — 6 — 4 — 2 — 1	0.0037	5.5179
		4 — 6 — 4 — 4 — 2 — 1	0.0021	**4.0452**
		4 — 6 — 4 — 3 — 2 — 1	0.0025	4.6141
		4 — 6 — 5 — 4 — 2 — 1	0.0033	5.7024

Table 2. Different NN architectures, regressions, and Principle Component Analysis (PCA) with NN in terms of MSE for sound pressure level prediction for aerofoil design

Training – Testing	Method	Architecture	Scaled MSE	Unscaled MSE
70% - 30 %	Neural Network	5 — 3 — 1	0.0062	10.7369
		5 — 3 — 2 — 1	0.0055	8.1798
		5 — 4 — 3 — 2 — 1	0.0039	6.6042
		5 — 5 — 3 — 2 — 1	0.0031	**5.0883**
		5 — 4 — 4 — 3 — 2 — 1	0.0033	5.3859
	Regression	Linear		25.53724
		Quadratic		25.11363
		Cubic		20.08023
	PCA with NN	4 — 6 — 4 — 2 — 1	0.0037	5.4129
		4 — 6 — 4 — 4 — 2 — 1	0.0027	4.7193
		4 — 6 — 4 — 3 — 2 — 1	0.0028	**4.1058**
		4 — 6 — 5 — 4 — 2 — 1	0.0037	5.2964

This plot gives an insight about visual representation of the data along with correlation between variables. The figure of the scatter plot matrix clearly shows a random

Table 3. Different NN architectures, regressions, and Principle Component Analysis (PCA) with NN in terms of MSE for sound pressure level prediction for aerofoil design

Training – Testing	Method	Architecture	Scaled MSE	Unscaled MSE
75% - 25 %	Neural Network	5 — 3 — 1	0.0056	10.5351
		5 — 3 — 2 — 1	0.0054	10.2200
		5 — 4 — 3 — 2 — 1	0.0044	6.7297
		5 — 5 — 3 — 2 — 1	0.0036	5.3320
		5 — 4 — 4 — 3 — 2 — 1	0.0028	**4.3825**
	Regression	Linear		23.78459
		Quadratic		19.87766
		Cubic		18.71646
	PCA with NN	4 — 6 — 4 — 2 — 1	0.0024	3.6856
		4 — 6 — 4 — 4 — 2 — 1	0.0024	3.6856
		4 — 6 — 4 — 3 — 2 — 1	0.0034	5.1138
		4 — 6 — 5 — 4 — 2 — 1	0.0021	**3.2747**

Table 4. Different NN architectures, regressions, and Principle Component Analysis (PCA) with NN in terms of MSE for sound pressure level prediction for aerofoil design

Training – Testing	Method	Architecture	Scaled MSE	Unscaled MSE
80% - 20 %	Neural Network	5 — 3 — 1	0.0070	12.3160
		5 — 3 — 2 — 1	0.0052	7.8561
		5 — 4 — 3 — 2 — 1	0.0055	9.4192
		5 — 5 — 3 — 2 — 1	0.0042	7.9350
		5 — 4 — 4 — 3 — 2 — 1	0.0032	**4.9800**
	Regression	Linear		23.87245
		Quadratic		19.85895
		Cubic		22.41482
	PCA with NN	4 — 6 — 4 — 2 — 1	0.0023	**3.9487**
		4 — 6 — 4 — 4 — 2 — 1	Non convergence	
		4 — 6 — 4 — 3 — 2 — 1	0.0035	5.0018
		4 — 6 — 5 — 4 — 2 — 1	0.0024	4.0019

relationship between the different parameters. As a result, a neural network is appropriate to handle the prediction problem.

In our experiment, first of all we shuffled the data rows. Thereafter, we scaled the whole data set using Max-Min scaling to have all the attribute values lying between zero to one. We ignored the data cleaning step as data already was cleaned. We used different Neural Network architectures to compare the results. Values represent number of neurons in each layer. We also tested all the network architectures against different proportion (60%-40%, 70%-30%, 75%-25%, 80%-20%) of training-testing ratio. Mean Squared Errors (MSE) are calculated for all the different Neural Network architectures against all the above mentioned training-testing ratio. We calculated MSE both on scaled output and on the output after unscaling. The results using different architectures are tabulated in Table 1 - Table 4. Table 1 contains the results with a training-testing ratio 60% - 40%, Table 2 with 70% - 30%, Table 3 with 75% - 25% and Table 4 contains the training-testing ratio with 80% - 20%. All four tables show that the better results can be achieved using a greater number of hidden layers.

We also modelled the same dataset using regression (linear, quadratic and cubic). MSE in all of these cases are calculated. The results of regressions are also tabulated in Table 1 - Table 4 along with NN results. From the results in Table 1 - Table 4, it is clear that Neural Network outperforms regression.

According to our study, the best configuration is with 5-4-4-3-2-1 network architecture with training-testing ratio as 75%-25%. The worst neural network performance is better than the best regression model.

Finally, we used principal component analysis to find out the principal components and the results are tabulated in Table 5. From the table it is clear that the first four components are important as the cumulative proportion of the first four components is as high as 96%. Figure 3 and Figure 2 present the importance of various principal components. After using the first four principal components as input to our neural network, results are improved. Among four different architectures against four training-testing combinations for each, in nine cases the PCA neural network hybrid outperformed the best neural network result.

Table 5. Importance of components

	PC1	PC2	PC3	PC4	PC5
Standard Deviation	1.452374	1.060189	0.9573568	0.8220337	0.4175374
Proportion of Variance	0.421880	0.224800	0.1833100	0.1351500	0.0348700
Cumulative Proportion	0.421880	0.646680	0.8299800	0.9651300	1.0000000

3 Conclusion

The self-noise of an aerofoil may lead to structural failure of a wing or a fan blade. It drastically reduces the fan blade efficiency, and further it affects the environment by

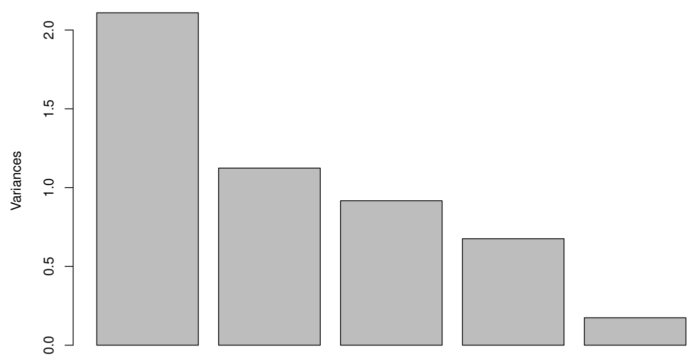

Fig. 2. Variance of the five principal components.

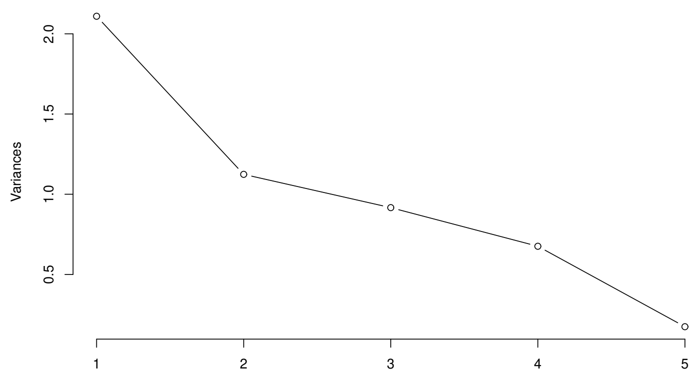

Fig. 3. Scree plot to show the variance of different principal components.

producing aerodynamic noise. Predicting aerofoil self-noise is a very important task as the overall behaviour of a system where blades or wings are used depends on it. In this paper we made an effort to apply different machine learning techniques. From our experiment it is obvious that a neural net performs much better than regression. Among regression techniques, quadratic regression performs better than linear and in most of the cases, cubic performs better than quadratic. After applying PCA and using only the important components in the neural network to predict aerofoil self-noise, performance becomes better than even the best neural network result. Although in our experiment we obtained significant results, there is scope for further experimentation. Regression with PCA can be used to compare results with ordinary regression. While applying PCA on the neural network, we ignored only the last component as the first four components have cumulative proportion of 97%. For further experimentation, the last two components can be ignored as the first three components have 83% of cumulative proportion. After that, results can be compared to draw further conclusions. In our present experiment, as the best result produces output with really high accuracy, the proposed method could be implemented practically to predict aerofoil self-noise. Overall this methodology has many advantages over conventional prediction methodology as this model can be used for any sets of aerofoils whether for a wing design or a rotor blade design.

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