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Identification of Sharp Edge Non-Slender Delta Wing Aerodynamic Coefficient Using Neural Network

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Abstract. Delta wing formed a vortical flow on its surface which produced higher lift compared to conventional wing. The vortical flow is complex and non-linear which requires more studies to understand its flow physics. However, conventional flow analysis (wind tunnel test and computational flow dynamic) comes with several significant drawbacks. In recent times, application of neural network as alternative to conventional flow analysis has increased. This study is about utilization of Multi-Layer Perceptron (MLP) neural network to predict the coefficient of pressure (C_p) on a delta wing model. The physical model that was used is a sharp edge non-slender delta wing. The training data was taken from wind tunnel tests. 70% of data is used as training, 15% is used as validation and another 15% is used as test set. The wind tunnel test was done at angle of attack from 0˚-18˚ with increment of 3˚. The flow velocity was set at 25m/s which correspond to 800,000 Reynolds number. The inputs are angle of attack and location of pressure tube (y/cr) while the output is C_p. The MLP models were fitted with 3 different transfer functions (linear, sigmoid, and tanh) and trained with Lavenberg-Marquadt backpropagation algorithm. The results of the models were compared to determine the best performing model. Results show that large amount of data is required to produce accurate prediction model because the model suffer from condition called overfitting.

1. Introduction

The search for faster speed and manoeuvrability on aircraft has led to the design of delta wing. However, flow physics on delta wing is complex due to its non-linearity. Non-linear flow can lead to many undesirable effects such as control instability and structural failure [1]. Many studies have been done in recent time to reduce these effects. Traditional methods of flow analysis such as wind tunnel test and computational fluid dynamic analysis are computationally expensive, not cost effective, and requires intensive power usage [2,3]. For these reasons, alternative method of aerodynamic flow analysis that requires less time, manpower as well as reducing cost is needed. Neural network is the perfect candidate for aerodynamic flow analysis because they do not rely on physical models or aerodynamic theories hence thorough knowledge of aerodynamics is not required. More importantly, neural network can be used to solve non-linear problems [4].

In recent time, variety of neural networks has been used in aerodynamic study such as convolutional neural network (CNN), support vector machine (SVM) and Multi-Layer Perceptron (MLP), their studies

are summarised in this section. Zelong et al. [5] uses CNN to predict aerodynamic coefficient of airfoil by mapping the airfoil geometry using signed distance function and using it as input. Meanwhile, Zhang et al. [6] proposed modification in the CNN architecture by combining matrix of airfoil geometry and flight conditions in one layer called "artificial image". Result from this model shows better predicting accuracy compared to vanilla MLP and traditional CNN model. For SVM, Mosbah et al. [7] uses extended geat deluge algorithm to optimize SVM parameters to decrease mean squared error in their ATR-42 wing analysis. The usage of SVM also extended to prediction of aerodynamic coefficient in unsteady condition such as demonstrated by Chen et al. [8] in which they uses improved version of SVM called Least Squared SVM. The usage of MLP to expand the database of aerodynamic coefficient was done by Gomec et al. [9]. In their study they utilise genetic algorithm to optimise the weight, bias, and mu coefficient of the MLP.

Delta wing needs to operate at high angle of attack to produce lift. But at high angle of attack, a condition called vortex breakdown which is when the vortex core of the wing stagnate and the vortical flow turn turbulent will occur. This condition can cause many undesirable effects. One way of studying this phenomenon is by analysing the pressure distribution on the wing. Hence, why coefficient of pressure is important in delta wing study. This study aims to predict C_P using artificial neural network. Three MLP networks were built with three different transfer function (linear, sigmoid and tanh) and the best performing network is determined.

Problem statement
Most studies focused on coefficient of lift (C_L), coefficient of moment (C_M), and coefficient of drag (C_D) and the physical model is airfoil. Studies relating flow analysis using neural network and C_P is lacking. This is because to measure C_P using wind tunnel, the physical model needs to be fitted with pressure taps which are difficult to install especially on small size model. Modelling C_P using CFD is complicated because it involves Navier Stokes equation. Therefore, this study is focusing on prediction of coefficient of pressure (C_P) on sharp edge non-slender delta wing.

2. Methodology
This section presents the proposed MLP network as well as the detailed procedure on the wind tunnel testing. MLP was chosen because of its abilities to generalize new data, learn conditional probabilities, being a universal approximators and most importantly the coefficients can be adapted using backpropagation technique. The separation of dataset is as follow, 70% of data used as training, 15% used as validation and another 15% used as test set. This ratio is found to produce best prediction result given the low amount of dataset used as input.

2.1 Wind Tunnel Test
The model that will be used in this study is a generic sharp leading edged delta wing UAV model. It was fabricated from aluminium and fitted with pressure taps. The relevant dimensions of the model are presented in Table 1.

Table 1. Wing Configuration

Part	Dimension
Length of Fuselage (core)	990 mm
Sweep angle	55°
Mean aerodynamic chord	493.7 mm
Core diameter	65 mm

The pressure taps are located on the surface of the model and they are evenly distributed on each wing. The pressure taps locations were coordinated such as: y/cr at 10%, 20%, 40%, 65%, 75% and 90% from the apex. The angle of attack can be changed by changing the pitch movement of the model or by moving the rear strut vertically. The drawing of the wing is presented in Figure 1. The red arrow

indicates the pressure taps which will capture the raw pressure data on the wing surface. The *x* and *y* coordinate of the taps will be used as input.
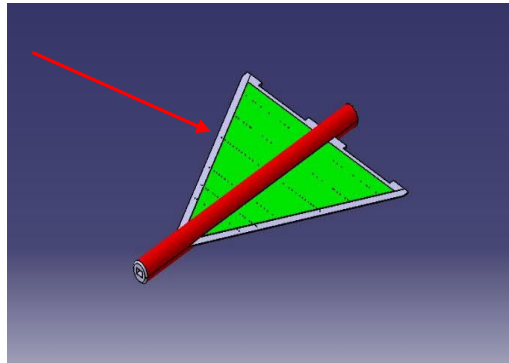

Figure 1. Drawing of the delta wing.

2.2 Data pre-processing

The data gathered from the surface pressure test is in the form of raw pressure data. The raw data needs to be converted into coefficient of pressure (C_P). After conversion, the data were plotted into CP-x/cr graph as shown in Figure 2. Data conversion was done using the following formula:

$$C_P = \frac{P - P_\infty}{\frac{1}{2}\rho^\infty v^{2^\infty}}$$

Where P is pressure at the pressure tap, P∞ is static pressure in the test section, $\rho\infty$ is density of air inside the test section, and v∞ is velocity of air inside the test section. Table 2 shows data sample that.

Table 2. Sample Data

y	x	Angle of attack	C_P
72	82	0	-0.05628
72	102	3	-0.21045
72	92	3	-0.2298
72	92	6	-0.39779
72	92	9	-0.51568
72	92	12	-0.5247

2.3 Modelling, training, and result

For this paper, MLP network structure with one input layer, two hidden layer, and one output layer was constructed. The experiment is done at angle of attack from 0˚-18˚ with increment of 3˚. The angle of attack and the *x* and *y* coordinate of the wing will be use as 'predictors' and the coefficient of pressure was used as 'response' for the model. This makes three neurons in the input layer. The first hidden layer consists of 20 neurons while the second hidden layer consists of 15 neurons. The output layer will be the coefficient of pressure of the wing model. The models will be trained using Lavenberg-Marquadt backpropagation.

3. Results

This section will discuss the wind tunnel result as well as results from the models with different transfer functions.

3.1 Wind Tunnel Results

Figure 2 shows the coefficient of pressure on the wing surface at $\alpha = 9°$ and $18°$. The two angles were chosen to represent moderate, and high angle of attack (α), respectively. At $\alpha = 18°$ the primary vortex formed at 20% of the apex while at $\alpha = 9°$ the primary vortex is formed at around 40%. This means the primary vortex shift upward as angle of attack increases. Lower angle shows no vortex formation.
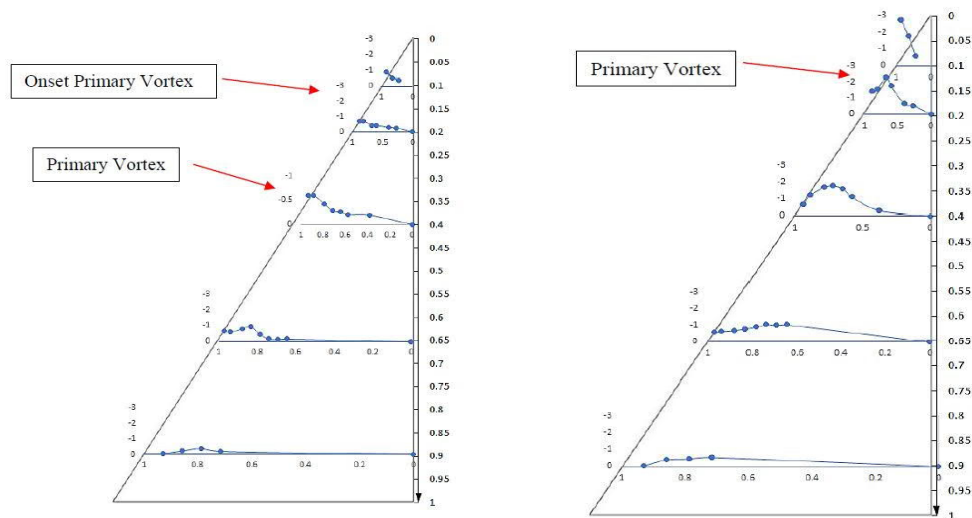

Figure 2. C_P graph at $\alpha = 9°$ (left) and $\alpha = 18°$(right).

3.2 MLP performance

The data from shallow MLP network shows that there is improvement in term of MSE data when sigmoid and tanh function was used compared to linear function. However, all three functions (linear, sigmoid and tanh) exhibit quite large error. This could be due the fact that only 196 set of data were used in which only 70% were used as training set while 15% were used as validation and other 15% as test sets. The tanh produced smallest error followed by sigmoid and linear. Linear function only took 1 epoch while sigmoid took 5 and Tanh took 10 epochs to finish training. It seems with small amount of data, the more complex the transfer function the longer it takes for the network to finish and produced larger error.

For comparison, data from study done by Secco et al. [10] is compared with data from this study. The dataset for Secco et al. [10] study is database for airfoil. The amount of data used is about 100,000 compared to only 196 that was used in the shallow network. The results shows the R value is far greater and the data fitted the regression line better. The MSE value is also better compared to the shallow network. Table 3 shows the comparison of the shallow models and Secco et al. [10] result. From Table 3 it can be concluded that with more training data, the model will become more accurate.

Table 3. Comparison of models

	MLP linear	MLP sigmoid	MLP tanh	Secco & Mattos, 2017 [10] sample result
MSE	0.10468	0.083814	0.075009	3.22×10^{-7}
R	0.72881	0.94619	0.94718	0.9989

4. Conclusion

An artificial neural network model of Multi-Layer Perceptron type was proposed to be used in this study. The networks were subjected to data gathered from wind tunnel to assist in flow analysis. Three shallow networks were constructed with each network utilising different transfer functions: linear, sigmoid and tanh. Each network was trained using Lavenberg-Marquadt back propagation and fitted with data from wind tunnel test. The results show that for model fitted with low amount of data, the more complex the transfer function the longer it takes to complete the training and the larger the error. However, the R value show different picture. The *R* value shows improvement when fitted with more complex transfer function. This indicates that the model is working but requires large amount of data and better weight and bias initialization is needed. Hence, the future direction will be in the direction of gathering more data and finding out ways to optimize the hyperparameters of the network. The data that was used in this study comes from the author previous work. Due to time constraint only, small amount of test was conducted hence the small amount of data.

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