An interpolation tool for aircraft surface pressure data

Problem presented by

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Problem statement

Airbus UK are concerned with designing efficient wings for aircraft. In the design process the aerodynamic load on the wing is calculated for various configurations including different Mach numbers and angles of attack. The aerodynamic load is calculated from the pressure profile around the wing. Airbus use a number of different methods to calculate the pressure, primarily CFD calculations and wind tunnel experiments. However, experiments and calculations cannot be performed for all configurations. Airbus asked the Study Group to investigate interpolation methods which incorporate wind tunnel and CFD data to calculate the aerodynamic load for many different configurations.

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1 Introduction

Airbus UK is a centre of excellence for wing design. The aerodynamic group calculates the aerodynamic loads on wings for different Mach numbers and angles of attack, to pass on to the structures group. The pressure data is obtained from several sources.

- Wind tunnel experiments provide a good source of surface pressure data but are expensive and can provide only a limited number of measurements.
- CFD calculations are used to calculate the pressure data by solving the Navier-Stokes equations. These calculations take several hours to run.

The aerodynamic group cannot perform wind tunnel experiments for all required configurations, and neither can they perform CFD calculations for all configurations. Therefore they propose to combine the multiple data sources to obtain data for a large number of configurations with a high level of confidence. Thus the problem presented to the Study group is to find a suitable means of combining the data from wind tunnel experiments and CFD experiments.

Airbus supplied, for use at the Study Group, wing pressure coefficient data obtained from both wind tunnel experiments and CFD calculations; see Figure 2. The data covered a number of Mach numbers and angles of attack at discrete points along several eta stations on the upper and lower surfaces of the wing; see Figure 1.

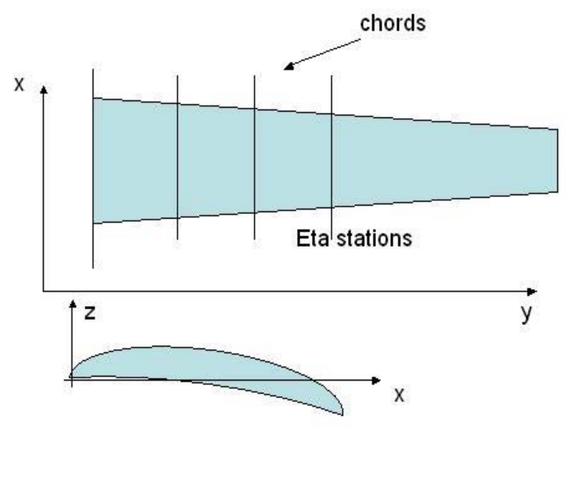

Figure 1: Diagram describing the layout of the wing and chords.

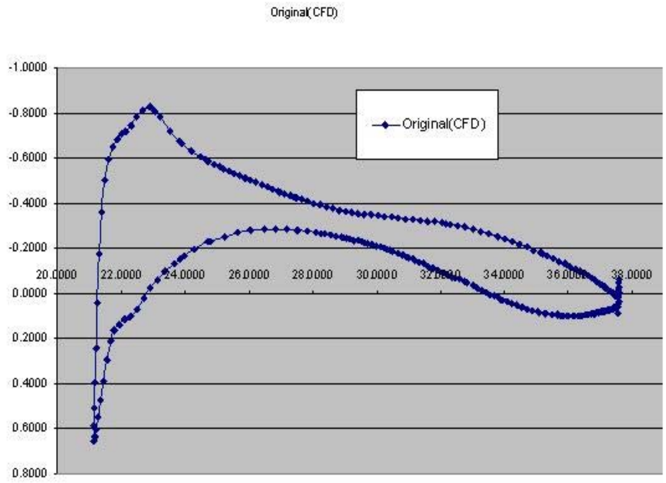

Figure 2: An example of the surface pressure coefficient data supplied by Airbus, calculated using a CFD package.

2 Neural Networks

An artificial neural network is essentially an adaptive computer programme which can simulate the relationships between sets of inputs and output variables. The simulation is achieved by a training process in which sets of inputs are applied to the network and the resulting sets of outputs are compared with known correct values, allowing automatic corrective modifications to network parameters. A general account of the technique has been given by R Beale and T Jackson, *Neural Computing: an Introduction* (Institute of Physics Publishing Ltd, 1992). The software used was a commercial neural network development tool Neudesk 2.11, provided as a free download by Neural Computer Sciences. This is Windows-based software with a spreadsheet-style data input section, which enables the configuration of a wide variety of network architectures and training algorithms.

2.1 Initial Test

In order to assess the suitability of neural networks to interpolate the pressure coefficient data, a network was trained on CFD data for one chord. The results from the output of the trained neural network were then compared with the original CFD data.

The network inputs were the x and z coordinates around the wing. The x coordinate runs along the length of the aircraft, the y coordinate runs along the length of the wing

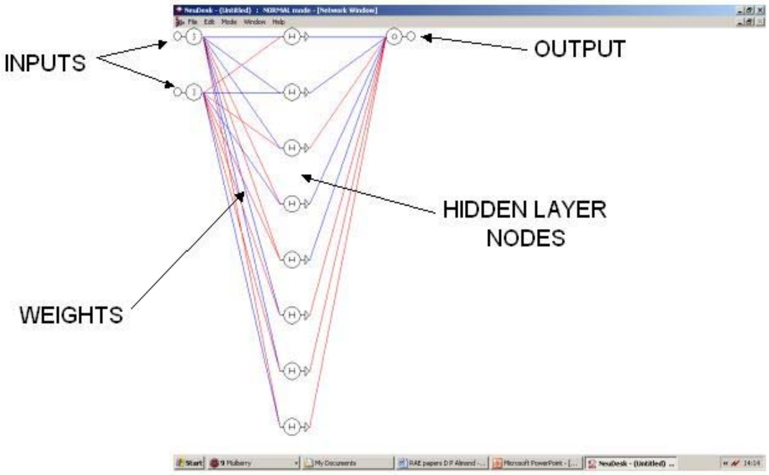

Figure 3: The layout of the nodes used in a trained neural network.

and the z coordinate runs perpendicular to both x and y. The network output was the pressure coefficient calculated at 288 points on the upper and lower surface of the wing. The network was trained to an average least square error of 1% using a hidden layer of 8 nodes and 24 weights. The results for the comparison can be seen in Figure 4.

The lift coefficient was calculated using the CFD data and the output from the trained neural network. The results are given in the table below.

Data Source	Value
CFD	0.3009
Neural Network	0.2976

Table 1: A comparison of the lift coefficient calculated using original CFD data and the output of a trained neural network.

Thus we can conclude that the neural network representation of data can provide an acceptable value for lift.

2.2 Neural networks for the entire wing

A neural network was then trained using CFD data for the entire wing, comprising 18 eta stations, each containing 288 data points. The neural network was trained using the x, y and z coordinates as an input against the CFD pressure coefficients as an output.

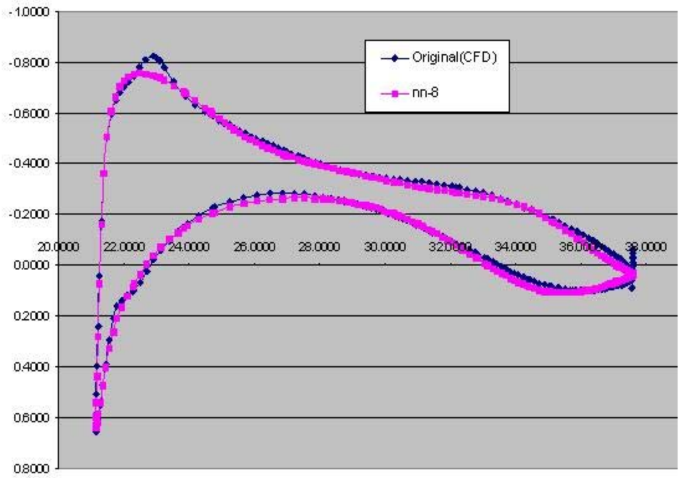

Figure 4: The plot of the output from the trained Neural network and the CFD calculations for one chord at one angle of attack and one mach number.

Networks were trained using 8, 10, 12 and 16 hidden nodes. However, the training was slow and produced errors greater than 8%. The plot of the trained neural network output against the CFD data, Figure 5, revealed the cause of the error and slow training times.

The trained network produced a poor fit to the data at chords close to the wing tip. The trained neural network results in a *cross over* of the pressure coefficient at locations where the x and z coordinates are close together.

This error was overcome by replacing the x coordinate input to the neural network by the arc length along the chord. This has the effect of separating the coordinates along the upper and lower surfaces. A neural network with a hidden layer of 20 nodes was trained with the new coordinate data for the same wing. The training remained slow, but the error reduced to 5% and produced the comparison with the original CFD data shown in Figure 6

2.3 Improvement

In order to improve the accuracy and reduce the training time for the network, the arc lengths for all chords were recalculated using locally normalised x and z coordinates. This eliminates the effect of the reduction in width of the chord along the wing. The network with 20 hidden nodes was retrained with the normalised data. The network was trained to an error of 2.8% in around 30 minutes on a laptop PC. The results for the

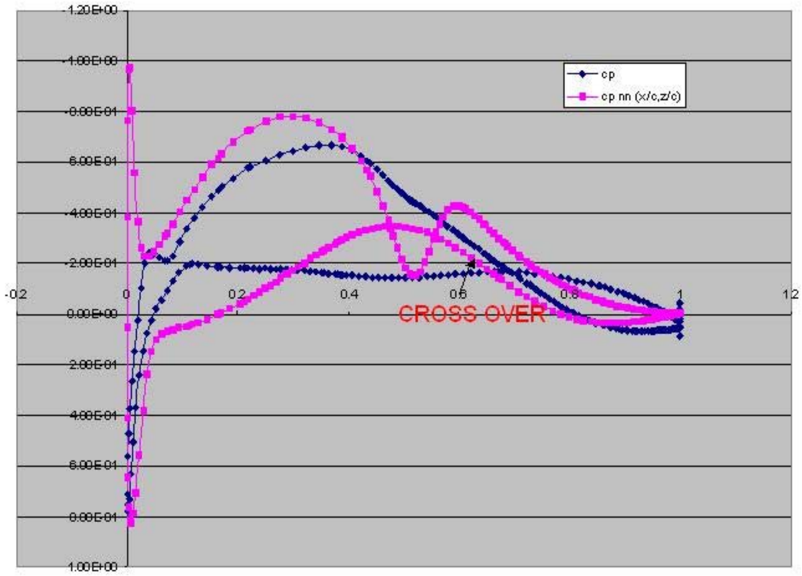

Figure 5: A plot showing the output at a single eta station of a trained neural network trained on data for a whole wing.

network compared with the original CFD data for chords along the wing are given in Figures 7, 8 and 9

3 Conclusion

Neural networks are a promising way of fitting and interpolating wing pressure coefficient data. They provide an easy-to-use technique that can be readily updated with wind tunnel data and data for differing angles of attack and Mach numbers.

3.1 Suggestions for further work

- A full investigation should be performed using state of the art neural network software in place of a 10-year-old free download.
- The networks should be trained on data sets for a range of angles of attack and Mach numbers.
- The wind tunnel data should be incorporated.
- Investigate ways of prioritising training on high-confidence experimental data.
- Comparison should be made with other interpolating methods, *e.g.* splines.

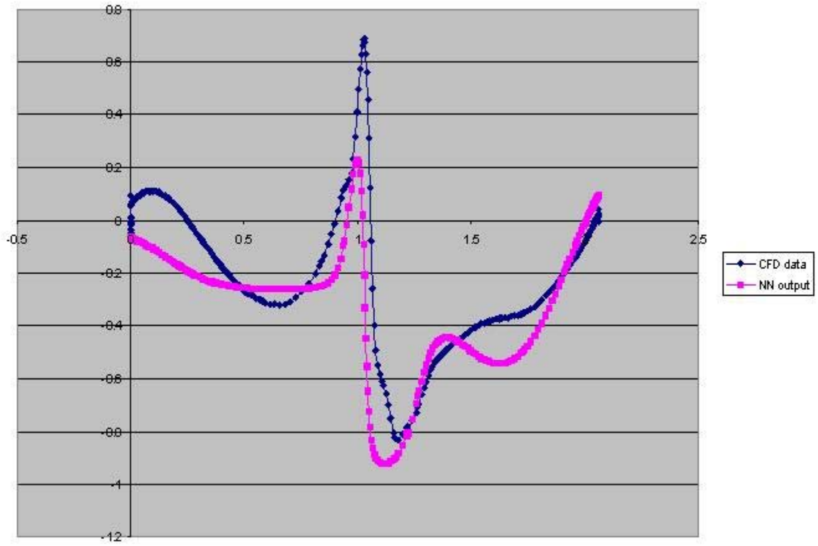

Figure 6: A comparison of the output from a neural network trained using arc length data

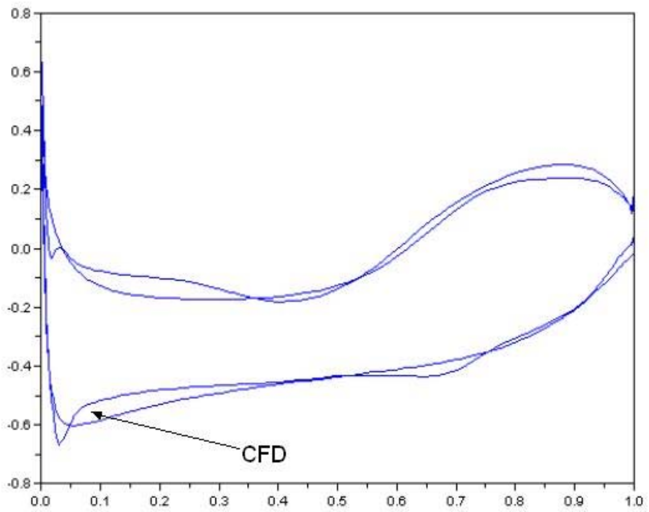

Figure 7: The output from a neural network trained using normalised arc length data at the wing tip.

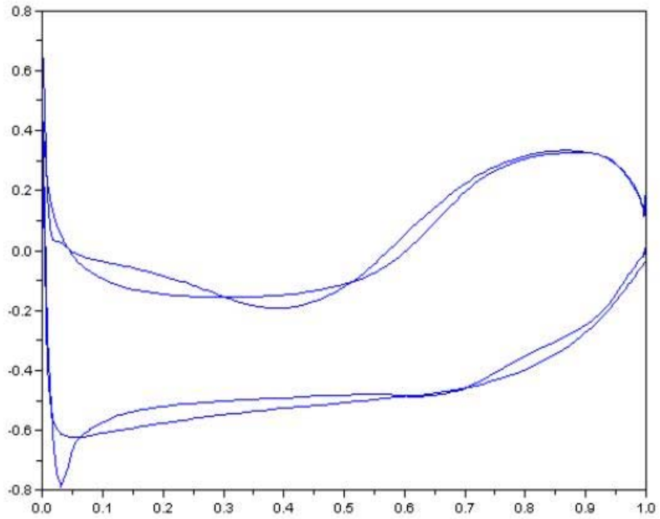

Figure 8: The output from a neural network trained using normalised arc length data at an eta station on the middle of the wing

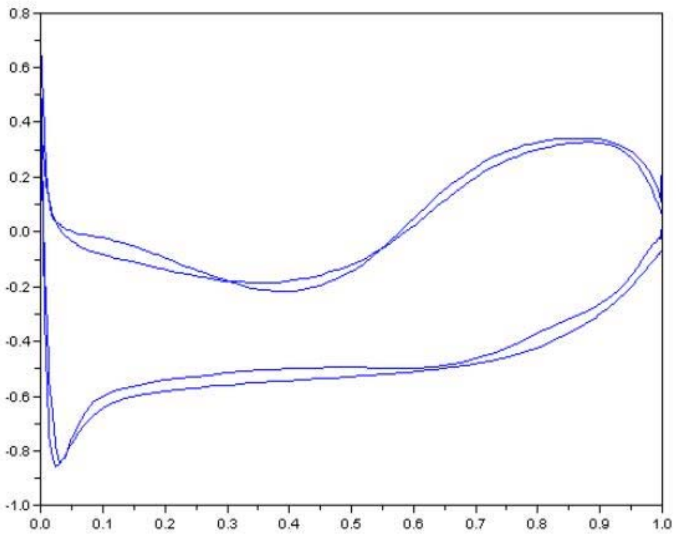

Figure 9: The output from a neural network trained using normalised arc length data at the wing root.