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Reducing Wind Tunnel Data Requirements Using Neural Networks

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13. ABSTRACT *(Maximum 200 words)*
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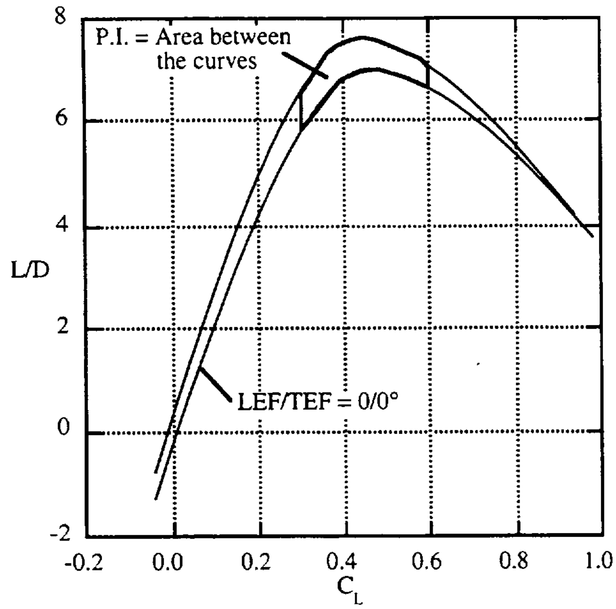


Figure 11. Definition of maneuver L/D performance index.

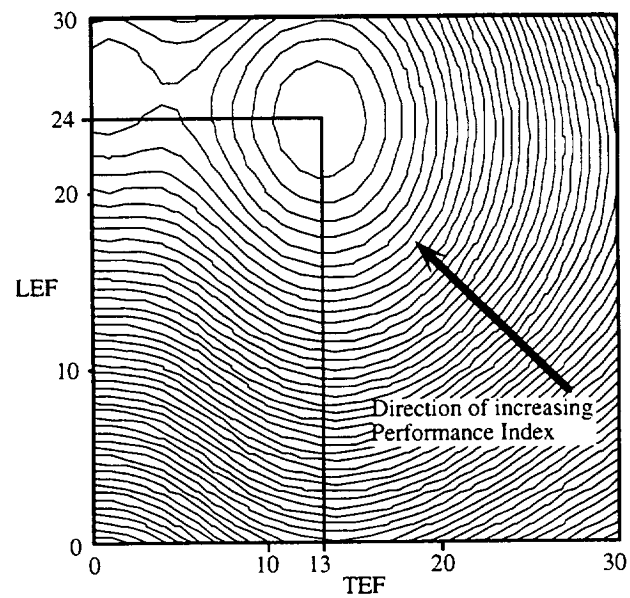


Figure 12. Contour plot of performance index. Performance index is maximized for LEF/TEF = 24°/13°.

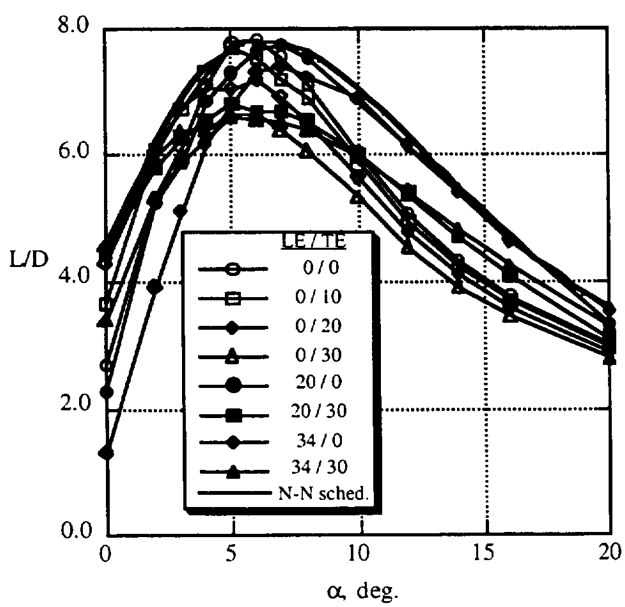


Figure 13. Cross plot of L/D measurements and neural-network model for flaps scheduled to maximize L/D across the angle-of-attack range from 0° to 20°.

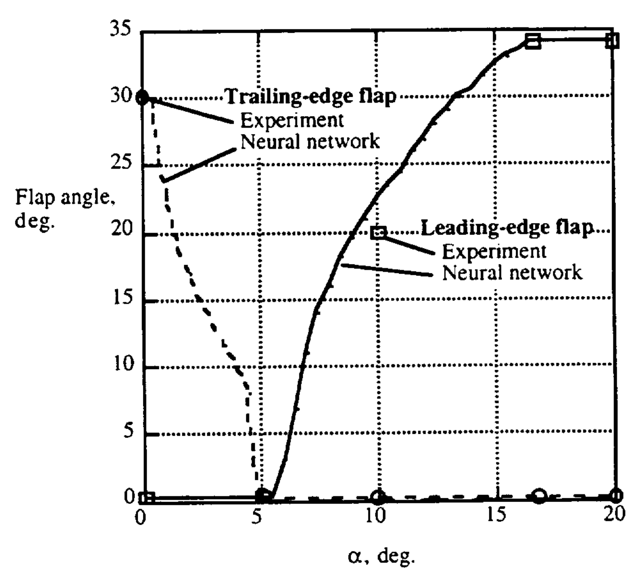
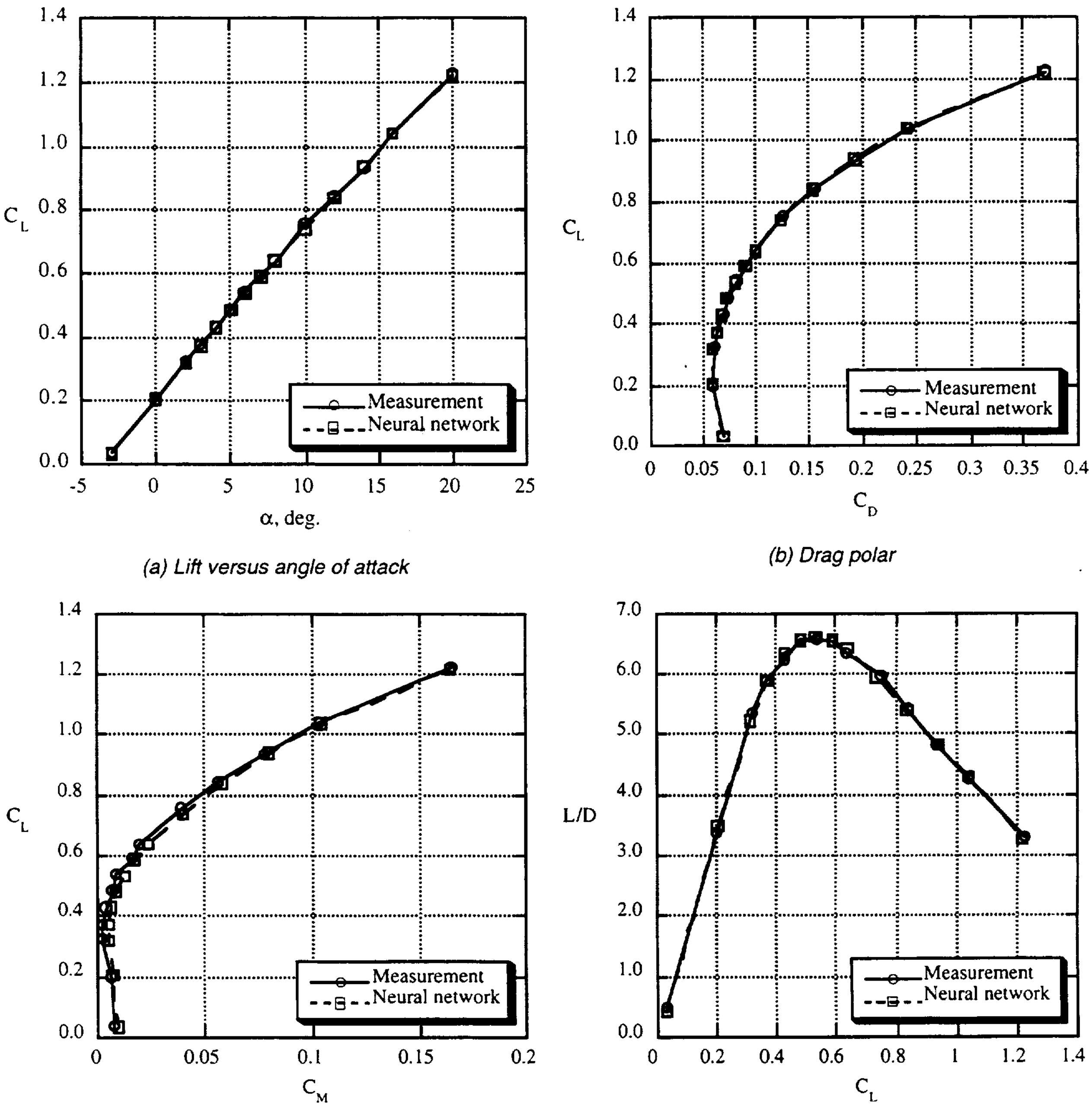


Figure 14. Flap schedule generated using neural-network model which maximizes L/D across angle-of-attack range from 0° to 20°.



(a) Lift versus angle of attack

(b) Drag polar

(c) Pitching-moment coefficient

(d) Lift-to-drag ratio

Figure 10. Comparison of predicted and measured aerodynamic characteristics for LEF/TEF = 34°/30°. Training set (fig. 9) does not contain this configuration.

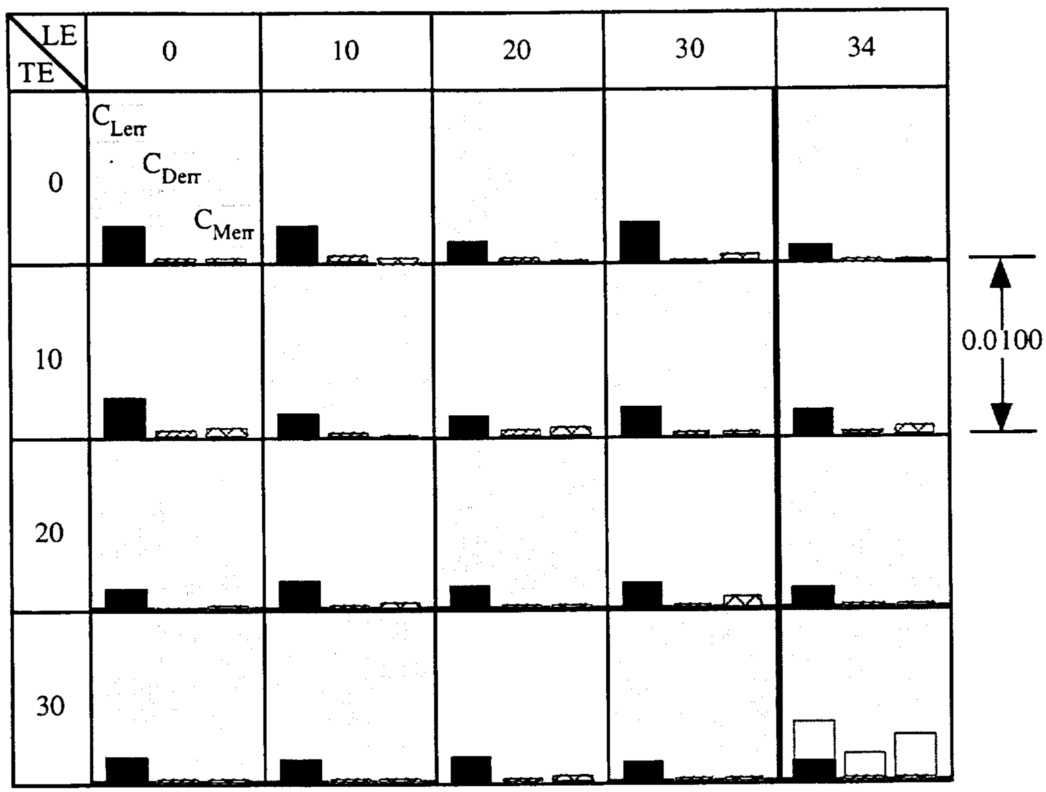


Figure 8. Error estimates for training set which accounts for nonlinear aerodynamic behavior of the SHARC model.

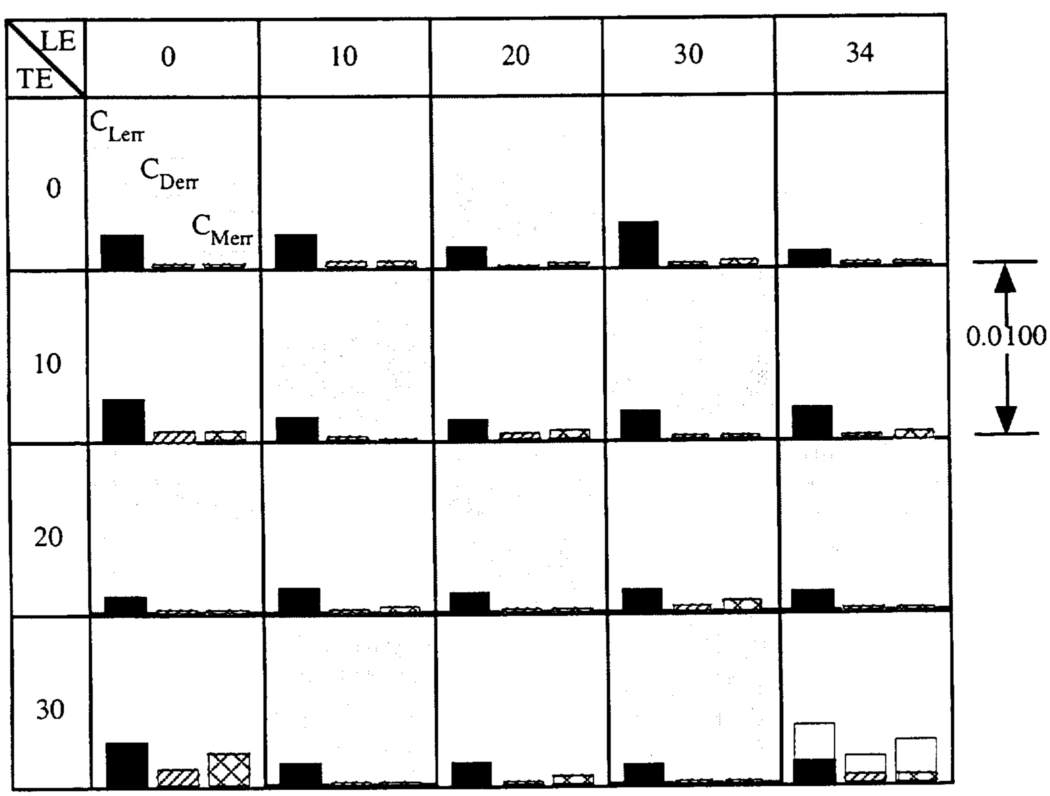
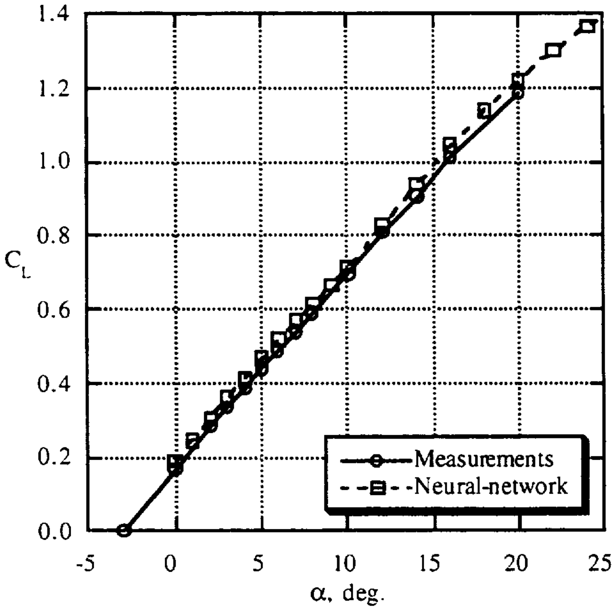
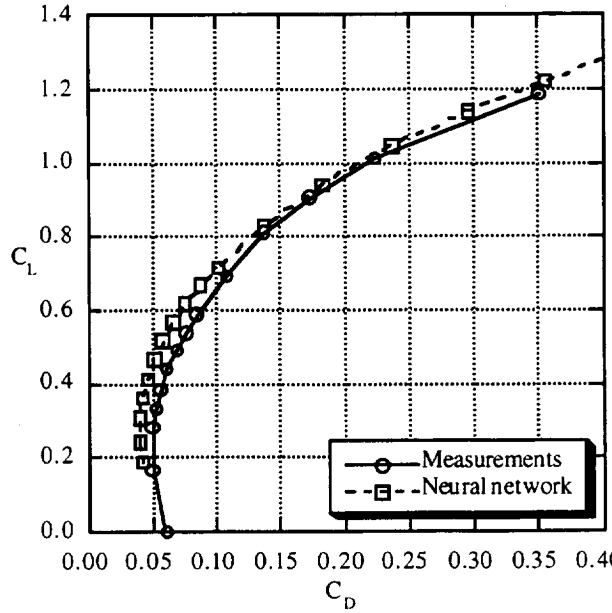


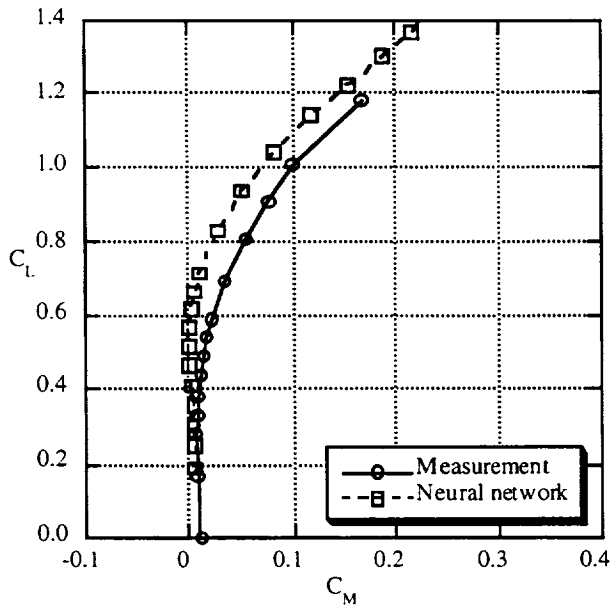
Figure 9. Error estimates for training set containing only 50% of the flap configurations which still accounts for nonlinear aerodynamic behavior of the SHARC model.



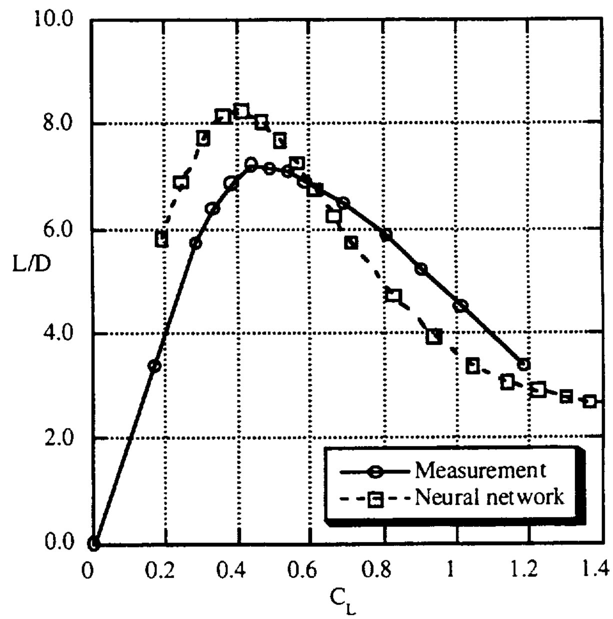
(a) Lift versus angle of attack



(b) Drag polar



(c) Pitching-moment coefficient



(d) Lift-to-drag ratio

Figure 7. Comparison of predicted and measured aerodynamic characteristics for LEF/TEF = 30°/20°. Training set (fig. 6) does not contain this configuration.

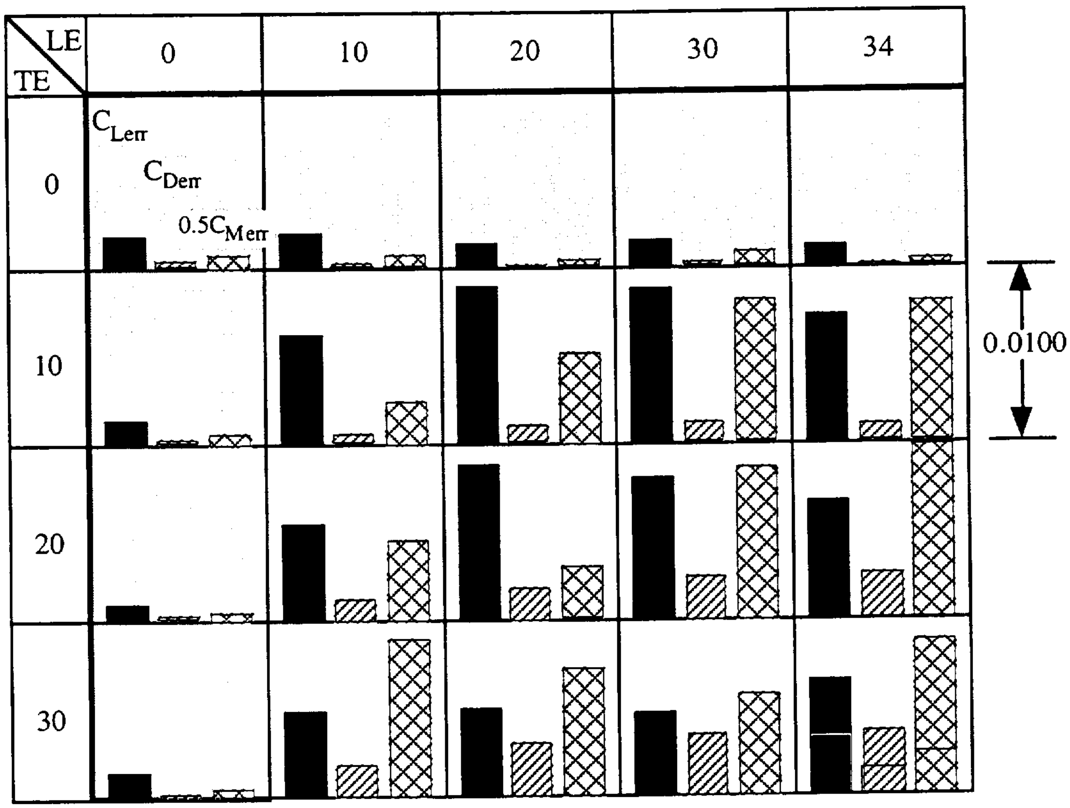
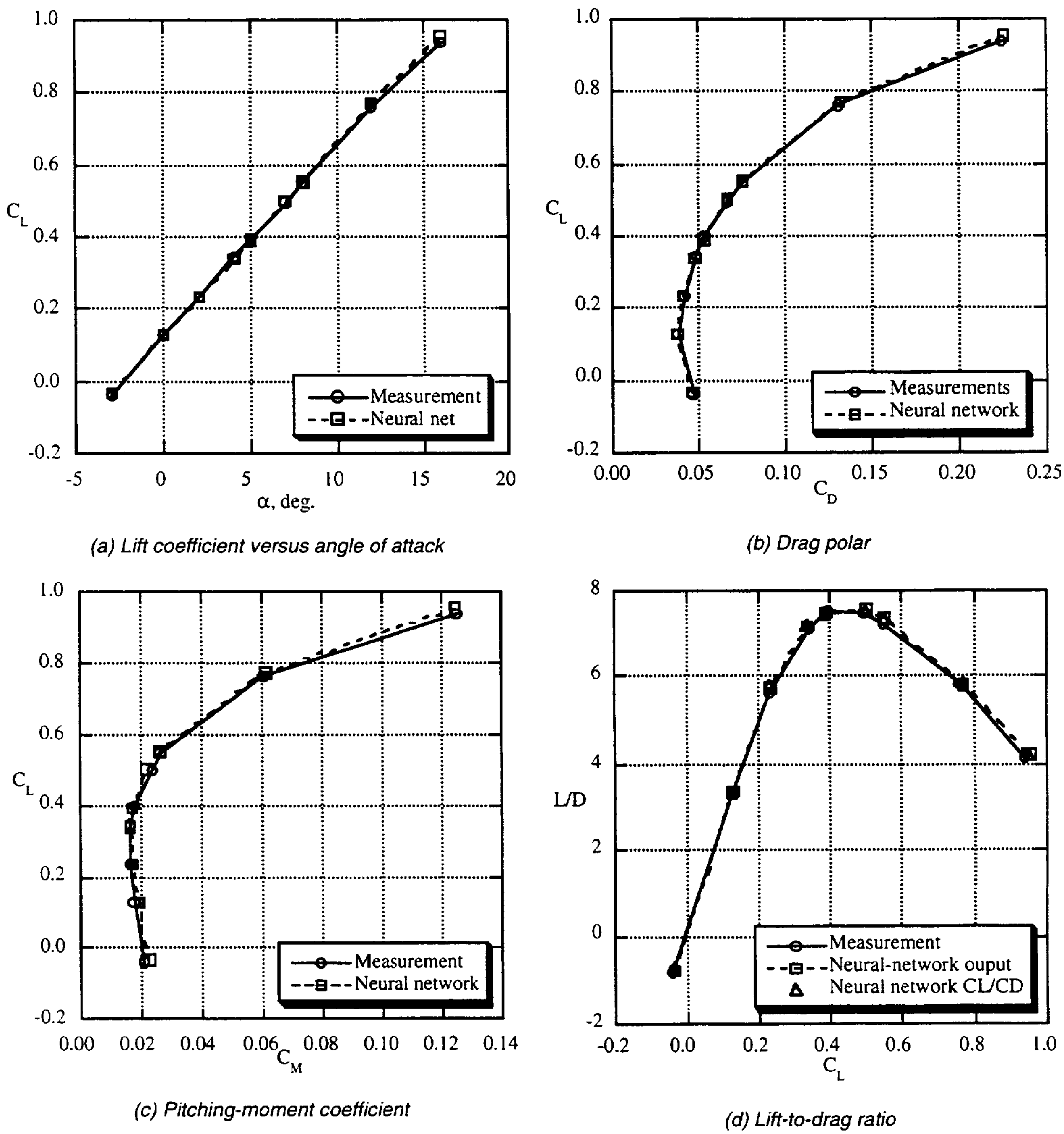


Figure 6. Training set which assumes linear aerodynamic behavior for leading- and trailing-edge flap deflections. Note that the error bars for pitching moment represent only one-half of that error.



(a) Lift coefficient versus angle of attack

(b) Drag polar

(c) Pitching-moment coefficient

(d) Lift-to-drag ratio

Figure 5. Comparison of predicted and measured aerodynamic characteristics for LEF/TEF = 15°/10°. Training set used, shown in figure 4, does not include this configuration.

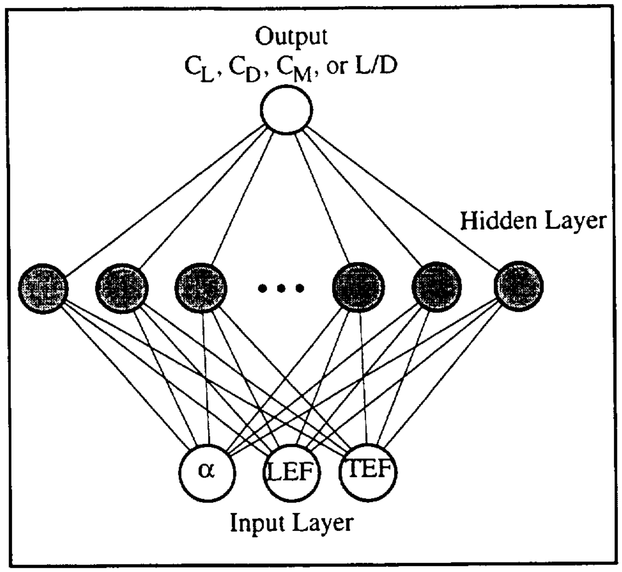
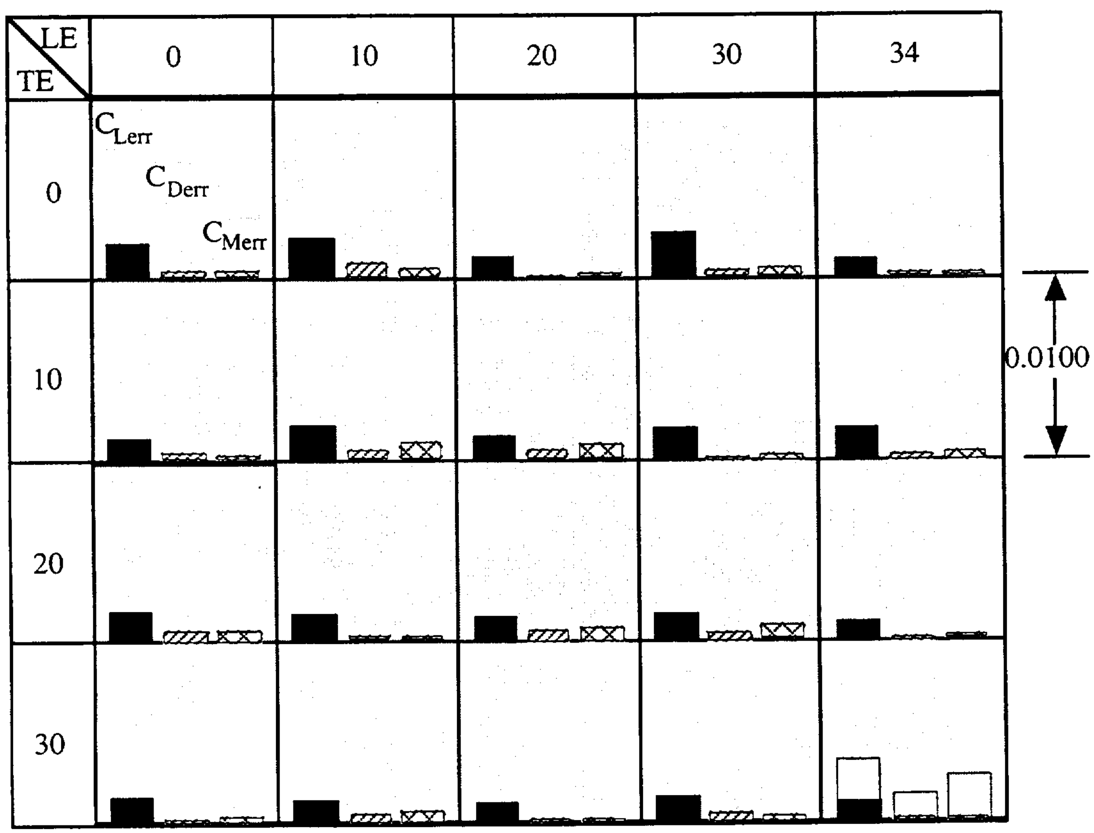


Figure 3. Neural-network architecture used for modeling aerodynamics.



Errors for LEF/TEF = 15°/10°: $C_{Lerr} = 0.0020$, $C_{Derr} = 0.0002$, $C_{Merr} = 0.0003$.
Errors for LEF/TEF = 30°/11.5°: $C_{Lerr} = 0.0016$, $C_{Derr} = 0.0007$, $C_{Merr} = 0.0015$.
Averaged rms errors for all geometries in training set: $C_{Lerr} = 0.0013$, $C_{Derr} = 0.0002$, $C_{Merr} = 0.0003$.

Figure 4. Summary of root-mean-square (rms) error from neural-network computation of aerodynamic coefficients. Shaded boxes indicate which flap configurations were contained in the training data. Experimental rms errors are shown as open bars in lower-left box.

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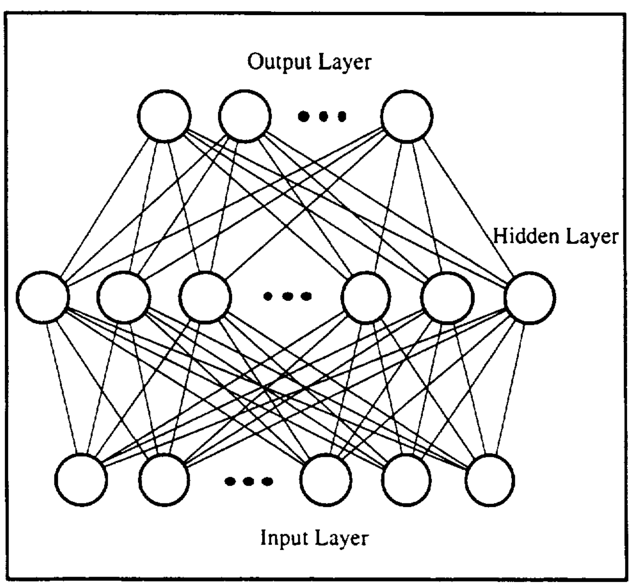

Figure 1. Simple neural network.

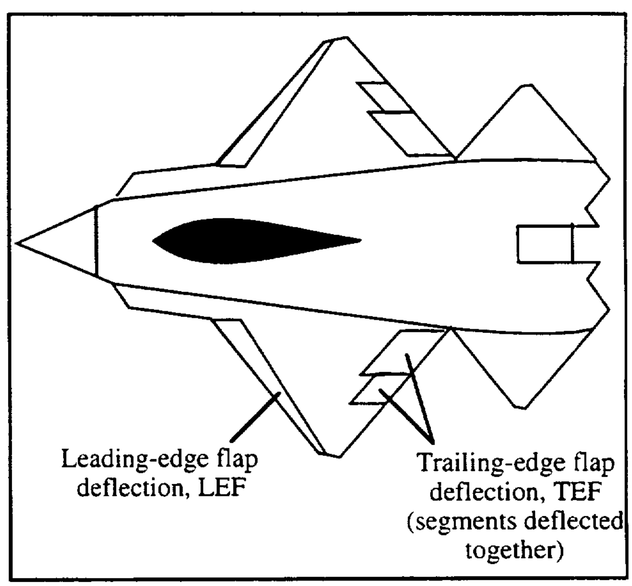

Figure 2. Plan view of SHARC model showing control surfaces tested.

Better selections of the configurations contained in the training set improve the accuracy of the model while still reducing the number of configurations relative to the full training set. Figure 8 shows one such selection and the resulting rms errors. This training set contains 60% of the flap configurations and predicts the aerodynamics of the configurations that are not in the training set to within the experimental error (unfilled rectangles in the lower-right box of fig. 8). Figure 9 shows the rms errors for a training set which contains only 50% of the flap configurations and still maintains predictive accuracy that is better than the experimental error. Figure 10 shows comparisons of the computed and measured aerodynamic coefficients for the 34°/30° flap configuration. The agreement is good in spite of the fact that the network is actually extrapolating outside of the range of the training set for both the leading- and trailing-edge flap deflections. Although risky, extrapolating slightly beyond the range of trained inputs did not lead to large errors in this particular example. The accuracy of the predictions obtained using the training sets shown in figures 8 and 9 demonstrates that neural-network techniques can be used to reduce the amount of wind tunnel data required to obtain an accurate representation of the aerodynamics of a given wind tunnel model.

Analysis of wind tunnel data after, or even during, a test is another area in which neural networks can significantly accelerate the aircraft design processes. An example of this use is in two different optimization procedures performed on the SHARC model. One of the objectives of the test was to examine the effect of vortex generators mounted onto various parts of the wing on the L/D behavior across a range of angles of attack appropriate for sustained maneuvers. A performance index was defined which, for a given combination of LEF/TEF, is given by:

$$\text{Performance index} = \left[\int_{0.3}^{0.6} (L/D)\,dC_L\right]_{LEF/TEF} - \left[\int_{0.3}^{0.6} (L/D)\,dC_L\right]_{0°/0°}$$

A graphical representation of the performance index is shown in figure 11. Finding the flap geometry which maximizes this performance index involved significant data analysis by a test engineer. The neural-network model, on the other hand, provided a very quick analysis to determine the flap angles which maximize this parameter and at the same time provided a more complete picture of how flap deflections influence performance. A contour plot of the performance index as a function of leading- and trailing-edge flap deflections generated using the neural model is shown in figure 12. The neural network predicted that the performance index is maximized when LEF/TEF = 24°/13°.

The second optimization performed on the SHARC model was to develop the schedule of leading- and trailing-edge flap angles which maximized the L/D at every angle of attack. This would normally be done by cross plotting L/D data from several runs and finding which leading- and trailing-edge flap-angle combination generates the highest L/D at various angles of attack. An example is shown in figure 13. The network model was used to directly determine the flap-angle combinations that maximize L/D at any desired angle of attack. The network prediction for the optimized L/D versus angle of attack is also shown in figure 13. The schedules for the leading- and trailing-edge flap angles are shown in figure 14 for the network model and from the traditional method of cross plotting the wind tunnel data. It is noted that there is little difference between the two flap schedules.

Conclusions

Wind tunnel testing of new airplane designs accounts for a significant part of the cost of the aerodynamic development process. Methods of reducing the amount of data acquired during a wind tunnel test would immediately reduce the cost of testing. The ability of neural-network models to fill in a design space for the flap deflections of a large-scale generic fighter model from sparse data was demonstrated. In the example shown, network models of the lift, drag, and pitching-moment coefficients as well as the lift-to-drag ratio produced accurate predictions when trained using only 50% of the data contained in the basic configuration test matrix. In addition, the resulting neural model of the aerodynamics provides a simple way to interrogate the entire design space allowing very flexible examination of configuration alternatives. The optimization of flap deflections using the network model to maximize the lift-to-drag ratio was demonstrated providing the same results as the traditional method of cross plotting data from numerous configurations. It is hoped that this technique will be employed during wind tunnel tests to determine when sufficient data have been acquired.

coefficients was also reported by McMillen et al. (ref. 2). A sketch of the network architecture used for the present study is shown in figure 3. In general, an increase in both the number of nodes in a given hidden layer and in the number of hidden layers in a neural network increases the accuracy of modeling nonlinear systems. For the work presented here, 15 nodes in a single hidden layer proved to be sufficient.

The three independent variables for this study were the leading- and trailing-edge flap deflection angles (LEF and TEF) and the angle of attack (α). The outputs were lift, drag, and pitching-moment coefficients (C_L, C_D, and C_M) and lift-to-drag ratio (L/D), which required a total of four networks. It is not strictly necessary to model L/D since the information is simply the ratio of C_L to C_D. Since L/D was an important parameter for the wind tunnel test, it was computed directly to increase the accuracy (errors are compounded when L/D is computed from C_L and C_D).

The ranges of the input parameters examined during the wind tunnel test were as follows: α from $-4°$ to 30° in various steps; LEF of 0°, 10°, 20°, 30°, and 34°; and TEF of 0°, 10°, 20°, and 30°. This gives a total of 20 flap configurations in the basic test matrix. Two other configurations were tested that are not shown in the matrix: LEF/TEF = 15°/10° and LEF/TEF = 30°/11.5°. These two configurations were not included in the training of the neural networks but were used to assess the accuracy of the network predictions.

In order to determine the amount of data required to accurately train the networks, several different subsets (training sets) of the data were generated that included limited numbers of the flap configurations. Each time a flap configuration was tested, measurements were made at several angles of attack but not necessarily at the same angles. The number of angles of attack also varied for each flap configuration. In general, model changes take as much or more time in the wind tunnel than the acquisition of the aerodynamic data. The neural networks were therefore trained using data sets which contained various numbers of flap configurations but all of the angles of attack for each configuration. The accuracy of the networks was evaluated by computing the root-mean-square (rms) error of each aerodynamic coefficient. The deviations from the measured data were computed at each angle of attack for a given flap configuration from which the rms errors were computed. The errors should be low for configurations included in the training sets. Comparison of the network outputs for configurations on which the networks were not trained with experimental results yields an indication of the predictive capability of the network model.

Results

As expected, when the aerodynamic data for all of the 20 flap configurations were used to train the network models, the resulting accuracy was excellent for all of the configurations. Figure 4 shows a summary of the errors in the aerodynamic coefficients for all of the flap configurations. The shaded squares in the figure show which configurations were included in the training set (all 20 in this case) and the bars show the rms errors for the three aerodynamic coefficients. A bar as tall as a square corresponds to an rms error of 0.0100. The experimental data had uncertainties (standard deviation) of $\Delta C_L = \pm 0.0035$, $\Delta C_D = \pm 0.0015$, and $\Delta C_M = \pm 0.0025$. The unshaded bars in the lower-right corner of the figure show the uncertainties for all of the wind tunnel data. The network errors are well within the experimental uncertainty for all of the configurations in the matrix. The network errors for the two configurations not included in the full training set are also quite small:

for LEF/TEF = 15°/10°:
$C_{L_{err}} = 0.0020$, $C_{D_{err}} = 0.0002$, $C_{M_{err}} = 0.0003$

for LEF/TEF = 30°/11.5°:
$C_{L_{err}} = 0.0016$, $C_{D_{err}} = 0.0007$, $C_{M_{err}} = 0.0015$

A comparison of the measured and predicted aerodynamic coefficients is shown in figures 5(a)–5(d) for the 15°/10° configuration using the full training set of figure 4. The lift coefficient was very well predicted for angles of attack less than about 10° (fig. 5(a)), and the corresponding drag and pitching-moment coefficients are also accurately predicted (figs. 5(b) and 5(c), respectively). The L/D is accurately captured by the network model for lift coefficients below that for maximum L/D, whereas beyond L/D_{max} it is slightly overpredicted. The values of L/D determined directly from the neural-network model and from the network C_L and C_D values are nearly identical.

Several other subsets of the measured aerodynamic data were used to train the network. The training set shown in figure 6 is one way to reduce the data requirements and would be sufficient if the aerodynamics of this airplane model changed in a linear fashion with flap deflections. This training set contains 40% of the flap configurations contained in the full training set. As is apparent from the error bars, the network model in this case did a relatively poor job of predicting the performance of flap configurations for which it had not been trained. The predicted and measured aerodynamic coefficients for the 30°/20° configuration (not in the training set) are shown in figure 7. The agreement is poor, as expected from the rms errors shown in figure 6.

changes during flight (e.g., due to damage to an airplane in flight) (ref. 6).

The current study was undertaken to directly examine how much wind tunnel data are required in order to train a neural network to predict the aerodynamic performance of a fighter configuration with an accuracy comparable to the experimental accuracy. Complete descriptions of the operation of neural networks are available in many references (see ref. 7). In general, the type of network we used (multilayer perceptron) consists of a number of nodes (often referred to as neurons) arranged in layers. A sketch of a simple network is shown in figure 1. The input nodes pass the input data to the hidden layer of nodes, each of which apply a nonlinear transfer function to the weighted sum of the inputs and pass along the result to the output layer with its own set of weighting factors. A network can contain any number of input, hidden, and output nodes. There may also be more than one hidden layer of nodes. This form of neural network is capable of approximating any continuously differentiable function (ref. 7).

The values for the individual weighting factors are determined by means of a training procedure in which many sets of inputs with known outputs are fed to the input layer. The weighting factors are adjusted iteratively to minimize the errors in the outputs (difference between the computed and known values). Many algorithms are available to adjust the weighting factors. Once trained, the network can then compute outputs to sets of inputs that it has not been trained on. If the training is successful, the outputs accurately predict the behavior of the system for any inputs.

The work described in this paper was undertaken with the goal of minimizing the amount of data required from wind tunnel tests. The idea is that while a test is in progress, a neural network is trained using the aerodynamic data as they are obtained. The network then predicts the results of the next run with different geometry or test conditions based on the "knowledge" that it has obtained up to that point. To be effective, the network must gain sufficient knowledge about the model so that the predictions match the measured results to within the accuracy of the measured wind tunnel data before the entire test matrix has been run. With this trained network, the aerodynamics of the model can be computed for both tested and untested conditions.

There are numerous other uses of a neural network trained to compute aerodynamics. For example, trained neural networks would provide a very simple way to interrogate an experimental database. This ability eliminates the need to interpolate the data across numerous variables. The network computations can be done using a desktop PC without using the aerodynamic database at all. Only the weighting factors need to be stored by the computer along with the information concerning the architecture of the trained network. The trained network model can be programmed (e.g., in C) and linked to any desired analysis or optimization code. Such a capability has obvious benefits for sharing data between various groups and when rapid computation of aerodynamic forces and moments are required for flight-simulation tasks.

Neural-network modeling can also identify bad or unexpected data during a wind tunnel or other kind of test. As measurements are compared with neural-network predictions, anomalies become readily apparent and test parameters can be modified to check whether the measurements are in error or the network needs additional training. The modeling capability can also facilitate tailoring the test matrix to increase the density of the test matrix where required. Areas of high gradients may be made more apparent during a test by use of the neural network than by other analyses of the data.

This paper describes the application of a particular neural-network methodology to modeling the aerodynamics of a large-scale wind tunnel model. The Subsonic High-Alpha Research Concept (SHARC) program was conducted jointly by the U.S. Air Force Wright Aeronautical Laboratory and NASA in the 40- by 80-Foot Wind Tunnel at NASA Ames Research Center. The program tested both 10% and 55% scale models of a generic advanced fighter aircraft (fig. 2) (refs. 8 and 9). The test program included the determination of the flap scheduling (leading and trailing edge) that gave the highest lift-to-drag ratio over the maneuver angle-of-attack range. In order to accomplish such a task, a large number of flap-deflection combinations had to be tested. This large set of aerodynamic data provided an excellent opportunity to examine the capabilities of the neural-network methods, particularly regarding the ability to obtain very high levels of modeling accuracy with limited training data. The work presented here is for the 55% scale model results.

Approach

Previous publications present details of the neural method used here to model aerodynamics (see ref. 10). In summary, individual 3-input, 1-output networks were used to model each of the desired aerodynamic coefficients. A Levenberg-Marquardt training scheme was used because it provided better accuracy than the more prevalent back-propagation training method. The single output networks for each of the aerodynamic coefficients provided more accurate modeling than multiple-output networks. The need for individual networks for modeling aerodynamic

Reducing Wind Tunnel Data Requirements Using Neural Networks

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Summary

The use of neural networks to minimize the amount of data required to completely define the aerodynamic performance of a wind tunnel model is examined. The accuracy requirements for commercial wind tunnel test data are very severe and are difficult to reproduce using neural networks. For the current work, multiple input, single output networks were trained using a Levenberg-Marquardt algorithm for each of the aerodynamic coefficients. When applied to the aerodynamics of a 55% scale model of a U.S. Air Force/NASA generic fighter configuration, this scheme provided accurate models of the lift, drag, and pitching-moment coefficients. Using only 50% of the data acquired during the wind tunnel test, the trained neural network had a predictive accuracy equal to or better than the accuracy of the experimental measurements.

Nomenclature

c	wing reference chord length
C_D	drag coefficient, D/(qS)
C_L	section lift coefficient, L/(qS)
C_M	pitching-moment coefficient, M/(qSc)
D	drag force
L	lift force
L/D	lift-to-drag ratio, C_L/C_D
LEF	leading-edge flap deflection angle
M	pitching moment
q	dynamic pressure, $(\rho V^2)/2$
S	wing reference area
TEF	Trailing-edge flap deflection angle
V	velocity

Subscripts

err	root-mean-square (rms) error
max	maximum

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Introduction

Wind tunnel testing is an integral part of the design of all airplanes (as well as most automobiles and trucks). Since the aerodynamic performance of an airplane is nonlinear due to the effects of viscosity, there is a need to test a large number of conditions and geometries. Test parameters typically include such things as control-surface and/or high-lift system deflections, variation in the angles of attack and sideslip, and velocity (Mach number) variations. The result is a long and expensive test program with a large amount of data to sort through and interpret. Subsequent analysis of the data is time consuming, typically consisting of a large number of cross plots to develop an understanding of how all of the geometric variations change the aerodynamic forces and moments as a function of angles of attack and sideslip. The resulting aerodynamic database is used to analyze the airplane's performance throughout its operating envelope as well as in-flight simulations to assess handling qualities before the airplane is built. Because of the large expense associated with wind tunnel testing and the subsequent analysis of the aerodynamic data, technologies which reduce these costs (without sacrificing accuracy) can significantly increase the profitability of a new airplane.

Simply stated, the problem that we addressed is how to reduce the amount of wind tunnel data required to completely define the aerodynamic performance of a given model to the desired accuracy. The ability of neural networks to accurately learn highly nonlinear, multiple input/output relationships makes this a promising technique for modeling of aerodynamic test data. This sort of curve (or surface) fitting offers the most likely path to minimizing data requirements.

There has been considerable interest recently in aeronautical applications of neural networks. In an early study, Schreck and Faller (ref. 1) successfully trained a neural network to predict the unsteady pressure variations on a pitching wing. This work demonstrated the network's capability to learn the behavior of a highly nonlinear aerodynamic system. Other applications have since been reported for characterizing flight-test data (refs. 2 and 3). Neural networks have also been applied to flight controls for defining control laws (refs. 4 and 5) and for updating control laws when aircraft performance