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Prediction of Aerodynamic Characteristics Using Neural Networks

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Abstract: This study presents a systematic neural network approach for the prediction of aerodynamic characteristics from the wind tunnel test data. The research is based on the Back propagation neural network method/radial basis function neural network method, which uses information about alpha, frictional drag coefficients and Mach number. A simple Backpropagation network of two input nodes (for the graph parameters), three hidden layers (18, 28, 10 neurons) and one output node was developed and compared with a radial basis function for the predicting power. For a training set of 136 data points and a training set with Mach number ranging from 0.6-3, the radial basis function neural network consistently out-performed the Backpropagation network regression model in time effectiveness. The results from the Backpropagation network and the radial basis function neural network are compared with the graphs taken from the database.

Key words: Wind tunnel test, radial basis function neural network, Backpropagation neural network, mach number

INTRODUCTION

Aerodynamics is the study of forces and the resulting motion of object through the air. Aerodynamic configuration sizing is conducted to develop the configuration geometry and the dimensions of the missile. Aerodynamic characteristics depend on individual aircraft design variables. Wind tunnels play a major role in the design and development of space vehicles. Frank H. Wenham is generally credited with designing and operating the first wind tunnel, in 1871. A wind tunnel test program was undertaken to define the stage separation aerodynamic environment. The wind tunnel apparatus is for studying the interaction between a solid body and an air stream. A wind tunnel simulates the conditions of an aircraft in flight by causing a high speed stream of air to flow past a model of the aircraft being tested. The model is mounted on wires so that lift and drag forces on it can be measured by measuring the tensions in the wire. In the Wind tunnel test the Mach number is an important factor. The graph is drawn for angle of attack (alpha) versus Coefficient of Frictional Drag coefficients (CDF) with the given Mach number as constant.

Nowadays, the neural network approach to data analysis has received much attention. Neural networks have overcome the theoretical limitations of perceptrons and early linear networks by the introduction of hidden layers to represent intermediate processing and to compute nonlinear recognition functions (Rumelhart, 1986). The rapid advancement of computing systems in the past decade has also contributed significantly to the success of this approach in various engineering, business and medical applications. Neural network systems learn to discriminate among equivalent classes of patterns within an input domain in a holistic manner. They are presented with training sets of representative instances of each class, correctly classified and they learn to recognize and predict other new instances of these classes. Learning is the phenomenon of readjusting weights in a fixed-topology network via different learning algorithms.

The neural network has been used quite successfully in various engineering and business applications such as analysis of appendicitis and cancer patient data (Weiss and Kapouleas, 1989) cancer image extraction and classification (Moallemi, 1991), studies of soybean diseases (Mooney *et al*., 1989) and in pharmaceutical applications such as pharmaceutical production development (Huussain *et al*., 1991), pharmacodynamic modeling (Veng-Pedersen and Modi, 1992) and pharmacological effects of drug concentrations (Erb, 1992).

This study analyses the neural networks for graph prediction. Aoyoma *et al.* (1990) present an application of the neural network approach to estimating quantitative structure-activity relationships. The neural network model performed better than linear multiple regression analysis. Backpropagation Networks (BPN) which are based on fully connected, layered, feedforward networks, in particular, have demonstrated the desirable properties of self-learning, noise-tolerance and good predicting power.

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In Data Mining in Soft Computing Framework (2000), Bodor experimented with a Backpropagation network for solubility prediction. The research showed the Backpropagation model to be superior to regression analysis technique in mean standard deviation for the training set. However, the neural network as well as the regression technique did not perform for an unknown set of organic compounds.

Forces of aeronautics: There are four primary forces that act on an airplane in flight are Thrust, Weight, Drag and Lift as shown in Fig. 1.

Weight is the force that measures the effects of gravity. Force must be generated that is stronger than the weight force. That force is called lift. The lift force is generated by air flowing over an object. The direction of the lift force will always be perpendicular to the direction that the air is flowing. When an airplane is on the ground not moving, there is not enough air flowing around it to create lift. Another force is needed to get the airplane moving through the air, so that the airflow can do its job of creating lift. This force is called thrust. Thrust propels an object in a particular direction, A jet engine generates thrust and because it is attached to the wing of an airplane, its thrust will be applied to the airplane. So as the engines thrust the airplane in the direction that they are pointed, air flows over and under the wings which creates the lift force. If enough lift is generated the airplane will fly. Drag is the force that resists any object trying to move through a fluid. The drag on an airplane is the result of, among other things, the energy needed to move the air out of the way of the airplane. Any motion or movement by the airplane will always be resisted by a drag force. The direction of the drag force is opposite to the direction of flight. The thrust force is aligned to counter the drag force. Reducing drag is one of the main concerns of aeronautical engineers when designing aircraft.

A method of computational simulation of the aerodynamic-or hydrodynamic-flow performance features of objects involves the use of neural-network mathematical models implemented in computer hardware. The method can be applied in conjunction with wind-tunnel, water-tunnel, or water-trough testing of scale models of such diverse objects as aircraft or parts of aircraft, sails, fins, turbine blades and boat hulls. In the case of an aircraft, for example, a neural network can be trained from: test input signals (e.g., positions of control surfaces, angle of attack, angles of roll, pitch and yaw, power settings and airspeed) and test output signals (e.g., lift, drag, pitching moment and/or other performance features). In general, the relationships between the input and output variables are nonlinear. The present method harnesses the ability of neural networks to learn nonlinear relationships between input and output variables. A neural-network model can be used to perform the nonlinear interpolation or extrapolation needed to predict the output variables for previously untested combinations of input variables. Moreover, the neural-network model can be generated during a wind-tunnel test and its predictions used immediately to focus the test conditions on input-variable combinations that have the greatest engineering significance; for example, the predictions can be used to "zero in" on control-surface settings that result in maximum lift. Thus, the method can reduce wind-tunnel test time, which can be expensive in the case of large wind tunnel.

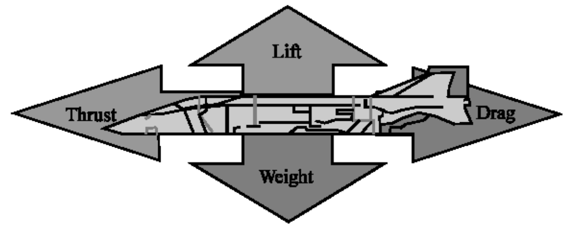

Fig. 1: Primary forces on an airplane

The coefficients present in the graphs of aerodynamics for wind tunnel test are Missile identity number Mach no

- Dynamic pressure.
- Angle of attack (Alpha).
- Control deflection.
- Normal force coefficient.
- Side force coefficient.
- Lift force coefficient.
- Frictional Drag Coefficient (Cdf).
- Pitching moment.
- Yawing moment coefficient.
- Rolling moment coefficient.
- Base pressure coefficient.
- Base drag coefficient.

A chamber through which air is forced at controlled velocities in order to study the effects of aerodynamic flow around airfoils, scale models, or other objects. The wind Tunnel has Settling Chamber, Contraction Cone, Test Section, Diffuser and Drive Section.

The purpose of the settling chamber is to straighten the airflow. The contraction cone takes a large volume of low velocity air and reduces it to a small volume of high velocity air without creating turbulence. The test section is where the test article and sensors are placed. The main forces to be measured in the test section are Lift and drag.

A force must be generated that is stronger than the weight force. That force is called lift. The lift force is generated by air flowing over an object. Drag is the force that resists any object trying to move through a fluid. Reducing drag is one of the main concerns of aeronautical engineers when designing aircraft. The diffuser slows the speed of airflow in the wind tunnel. The drive section provides the force that causes the air to move through the wind tunnel.

To study pressure, velocity distributions around bodies. The wind tunnel can be made use of to make modification to the body. To obtain the aerodynamic forces experienced by body. Aircraft, spacecraft, rockets, cars, trucks and buildings can be tested in wind tunnels.

Advantages of wind tunnels include reliable and consistent airflow, low turbulence, ability to make precise measurements and reproducible conditions and results.

NEURAL NETWORKS

Training of an ANN is the determination of connection weights and the threshold values of neurons in the network. These values are used for teaching the network for finding solution to a problem. This process is inspired from the brain's learning by experience. The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training. Basic structure of a training algorithm starts with initializing all weights. The input vector is applied to the network and the outputs are propagated from the inner layers up to the output layer. The output obtained from the network is compared by the desired output. The error is calculated and in backward fashion new weights are assigned to the neurons. All the operations from the forward output passing are iterated until a good solution, which is as close to the desired output, is obtained.

The research shows the potential for use of neural networks to become a useful analytical technique for graph prediction. The objective in using neural networks in graph prediction is to have the neural system learn to model a relationship that is represented explicitly in a set of historic data. Thus the objective is to predict a new aerodynamic characteristics graph by performing both interpolation and extrapolation. There are many factors that influence the performance of such decision support systems applied to wind tunnel test. In any Machine Learning system the competence of the systems will improve with the amount of training data available.

Artificial Neural Networks (ANNs) are very popular as classification or regression mechanisms in most of the decision support systems despite the fact that they are unstable predictors. This instability means that small changes in the training data used to build the model (i.e. train the ANN) may result in very different models. A central implication of this is that different sets of training data may produce models with very different generalisation accuracies.

The performance of feed-forward neural network trained with the backpropagation algorithm and radial basis function neural network for graph prediction on a wind tunnel test data is analyzed. The neural network techniques is applied for predicting a graph with a new Mach number purely from observing the raw input graph data with a variety of Mach numbers. A new model is thus developed for predicting graphs in wind tunnel test data. The neural networks used for analysis include Radial Basis Function (RBF) neural networks and Back propagation neural networks.

The major advantage of neural networks is error tolerance. The network is capable of finding a generalization for new or distorted data. A model is determined for each given data. In order to design an ANN, the number of layers, the distribution of the neurons to different number of layers, the communication used between the layers and the strength of connection within the network must be determined properly. The structure of an ANN is basically a topology consists of three layers: input, hidden and the output layer as given in Fig. 2.

The input layer is responsible for extracting knowledge from the environment. The output layer is responsible for the communication with the environment. The hidden layers are responsible for the execution between these two layers. Neurons are connected with unidirectional paths and each of them is communicated with other neurons in the same layer or in different layers.

GRAPH PREDICTION USING NEURAL NETWORKS

The objective of this study, is to predict the aerodynamic characteristics by using the concept of learning from examples. The first step in building a neural network application to predict the aerodynamic characteristics was to develop a test data set for the neural network to use in training itself (Fig. 3).

Define inputs and outputs: This module was used to choose which variables would be used as input variables

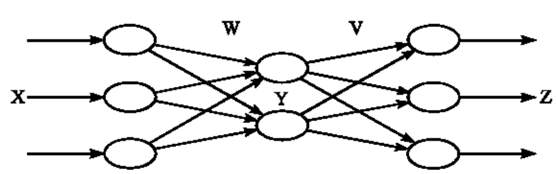

Fig. 2: Architecture of ANN

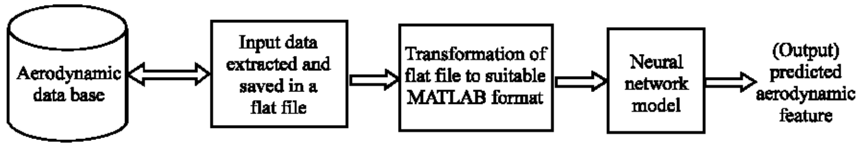

Fig. 3: Architecture for graph prediction

and outputs and to either specify or compute the minimum and maximum value for each variable. Input variables were used by the neural network to make the prediction or classification (the independent variables). The learning from examples concept is used for predicting the aerodynamic characteristics. The input variables used are the graphs angle of attack vs CDF for constant Mach number. Output variables (the dependent variables) contained the results the network was expected to learn in order to predict the graphs.

File extraction: From the data set population (inputs and results), test, training and production files were extracted. A test data set containing 136 data points for mach numbers 3.5,3, 2.5,1 and 0.6 was randomly extracted by the neural network to compute average training error used to determine when to stop training. A training set containing all the mach numbers data was used for network learning.

Architecture selection: A variety of neural network architectures are available to process the data from the input data set files. A multi layer backpropagation architecture and radial basis function were used for training because of its ability to generalize well when applied to a wide variety of applications and also for the ability to have better regression.

Learning: As the neural network software read the training set, the network learned the data patterns in the training set. Learning subprograms differ depending on the architecture selected. As training progressed, statistical graphs furnished by the neural net software, provided a means to monitor training progress.

Numerical historical data and repetitive examples in which the solution is already known are required to train a neural network. While the relationship between variables may not be known, network results can be improved by the addition of more variables. Data may need different representation, for example if data has a very large value range, logarithms or other data transformations or conversions may be necessary. Both the BPN and RBF Network architectures and their configurations are tested by trial and error until results are acceptable.

Implementation issues: The test data set is extracted from the ORACLE Database. But to train and test the different graphs with the mach numbers given above with Artificial Neural Network the data is converted into sample inputs as (*.dat) file format. A simple Backpropagation network of two input nodes (for the graph parameters), three hidden layers (18, 28,10 neurons) and one output node was developed. The back propagation neural network is used due to the ability to have better interpolation and extrapolation.

The program developed in this study will be utilized to perform neural net training. Inputs for the program are the learning set of data obtained from the flight manual. The following decisions regarding the neural network were also required as inputs:

- The number of inputs.
- The value for the learning coefficient.
- The number of processing elements in the hidden and output layers.
- The number of cycles for each run.

MATLAB was used as the modelling language to implement the neural network. In this MATLAB functions in the neural net toolbox. For example, initff initializes a feed-forward model, trainlm trains a network using Levenberg-Marquardt Algorithm. Other transfer functions will be employed in this section as well.

Radial Basis Function networks (RBF) is a type of artificial network for applications to problems of supervised learning e.g. regression, classification and time series prediction. Radial basis function networks are non-parametric models. By non-parametric models, it means that there is no a priori knowledge about the function that is to be used to fit the training set. An example of a parametric model would be fitting a straight line to a set of points. The form of the function a straight line, is known and it is just a matter of best fitting the line to the training set. RBF networks can be used to solve regression problems.

RESULTS AND DISCUSSION

This study effectively connects the Java front end design, Oracle database and MATLAB. The following steps were performed to connect Java with Oracle:

- Importing packages.
- Registering the JDBC drivers.
- Opening a connection to a database.
- Creating a statement object.
- Executing a query and returning a result set object.
- Processing the result set.
- Closing the result set and statement objects.
- Closing the connection.

MATLAB: In this project, we use MATLAB for Neural network and to plot graphs. Matlab is a software package for high performance numerical computation and visualization. The name MATLAB stands for MATrix LABoratory. It provides easy extensibility with its own high level programming language.

Steps to connect Java with MATLAB

- Importing packages.
- Registering the matlab engine engine.
- Opening a Connection to a MATLAB.
- Executing result set.

In this project the GUI design has the Model, X-axis, Y-axis, Attributes, Value, these values retrieved from the database. The design of GUI is shown in Fig. 4. The help about the Wind Tunnel is shown in Fig. 5. The training module can be selected from the GUI. The learning trial with Radial basis function based decision module is shown in Fig. 6. After retrieving the data from the Database, the data are stored in the files and are trained with suitable decision module. The plot to show the graphs predicted for Mach number 0.6, 1 and 2.5 by RBF neural network together with statistics is shown in Fig. 7 and 8.

The time for convergence in BPN and RBF neural network is shown in Fig. 9. A practical problem that occurred during training is that in the BPN Neural Network small changes in the training data set may produce very different models and consequently different performance on unseen data. In this study, we show that this instability means that estimations of the generalisation performance of an ANN for a particular task may vary considerably depending on the training data used.

It can be seen that as the training of the network proceeds the error on the training data continues to drop but after 200 epochs (200 presentations of all the training data) the error on unseen test data starts to rise. After this point the network is overfitting to peculiarities in the training data and is losing generalisation accuracy.

Up to a certain point additional training data will produce appreciable increases in accuracy. However, beyond the knee point in the graph additional data produces little increase in accuracy. At the knee point the learning system has seen a useful cross section of data samples that represent a good coverage of the problem domain (Fig. 10).

The solution to this problem is to hold out some of the available data from training and stop training when error on this validation set starts to rise. In situations where an abundance of training data is available, all the details of the problem will be well represented in the training data and overfitting is unlikely to be observed

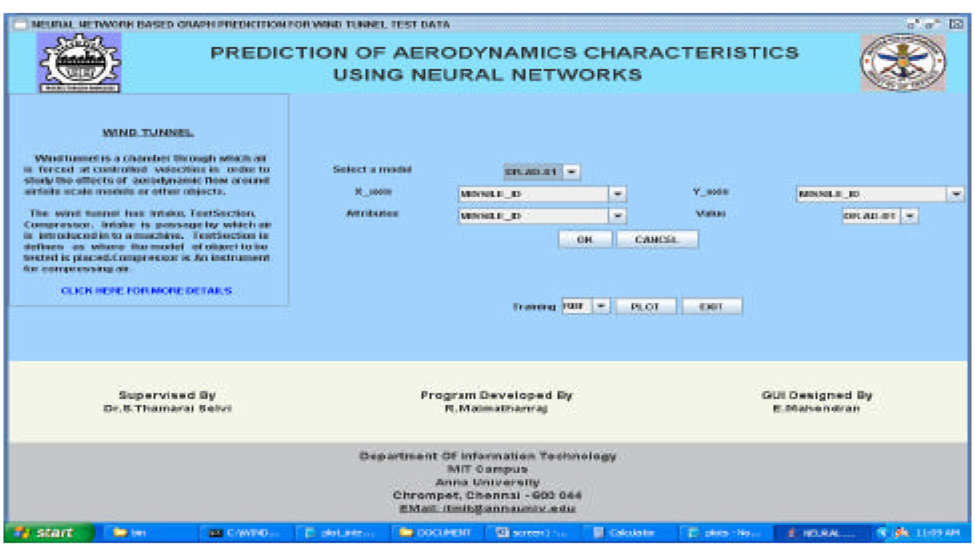

Fig. 4: GUI design for prediction of aerodynamic characteristics using neural networks

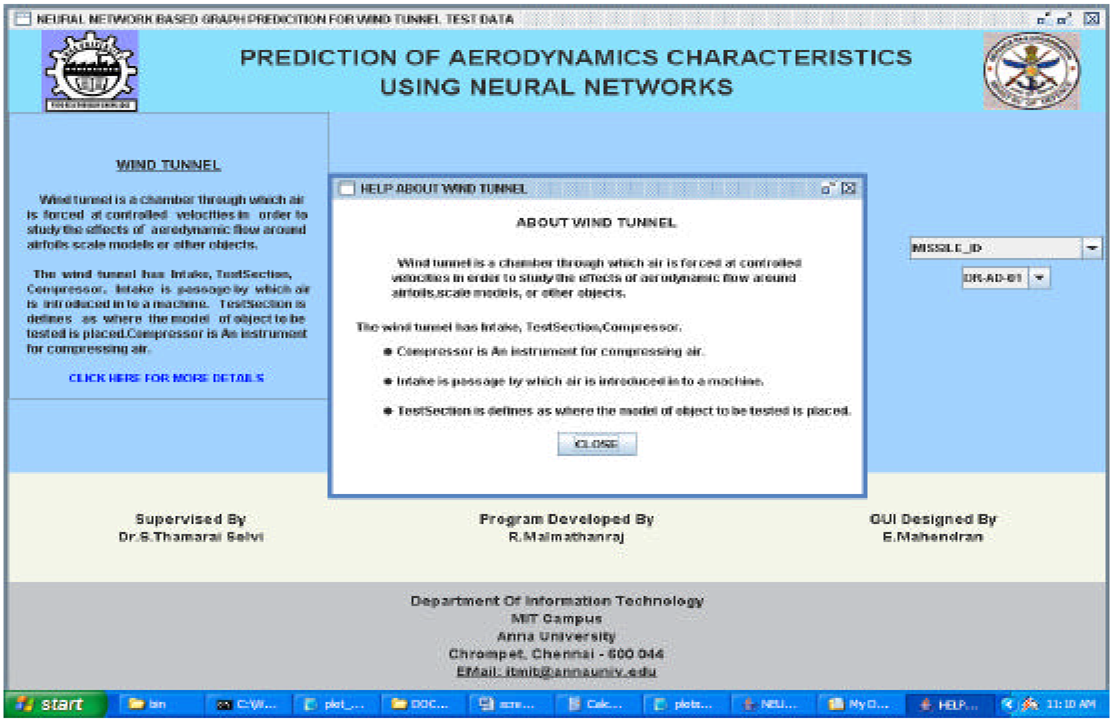

Fig. 5: GUI Design for prediction of aerodynamic characteristics using neural networks with help files

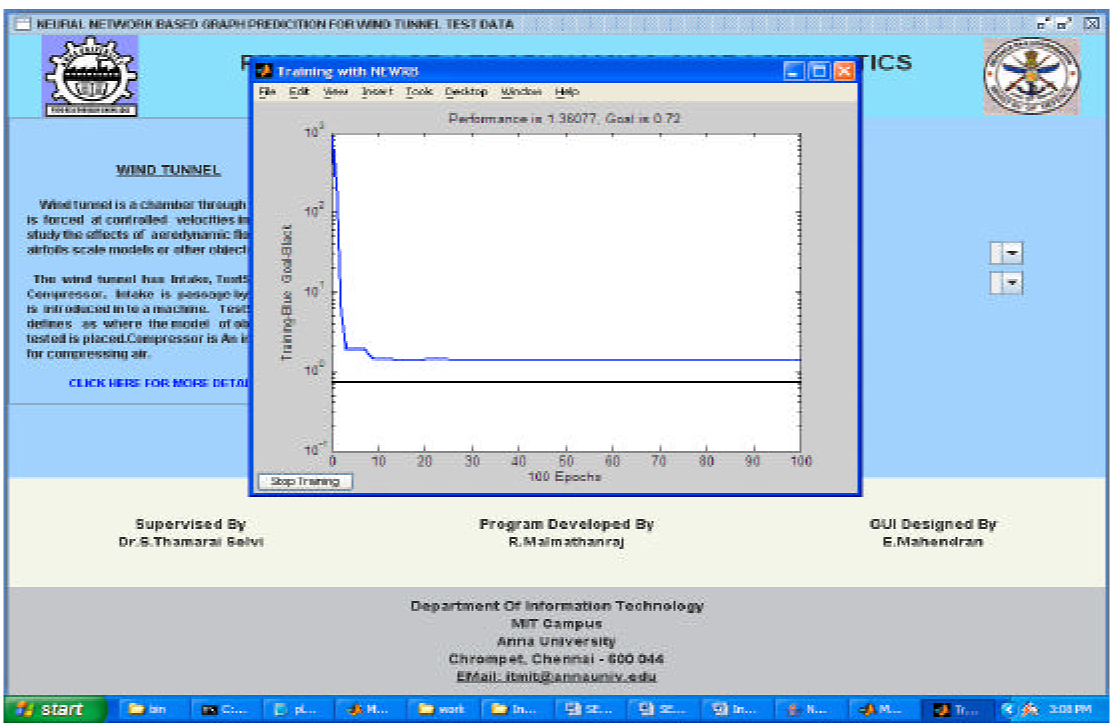

Fig. 6: Plot to show the learning trial of RBF neural network

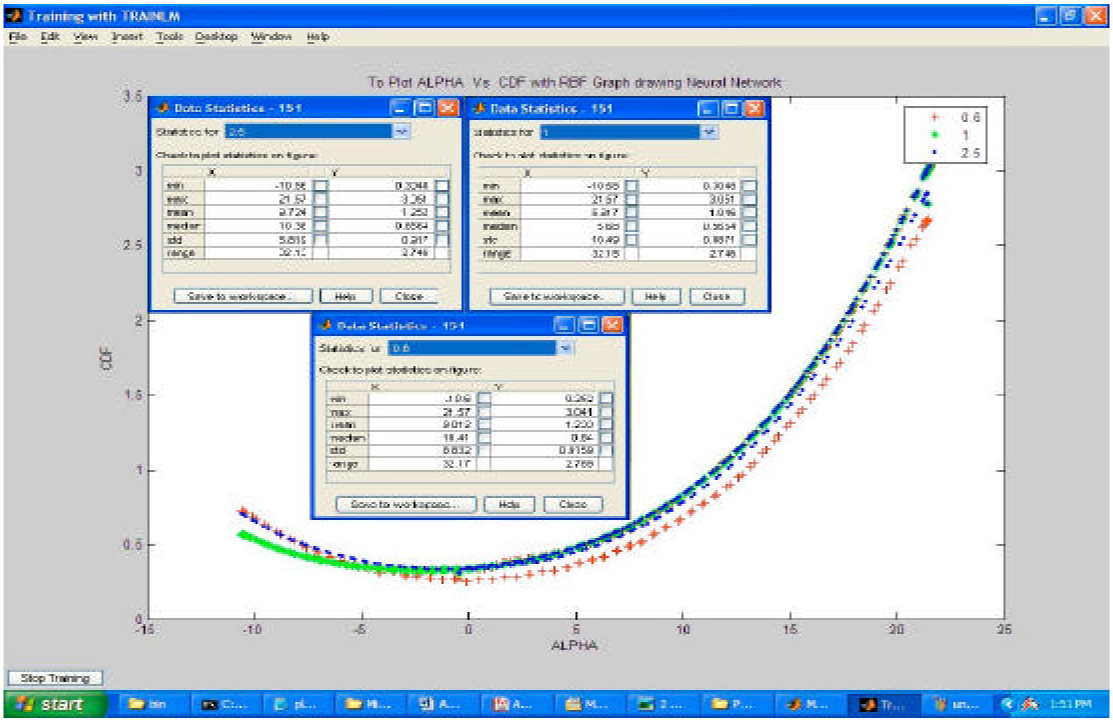

Fig. 7: Plot to show the graphs plotted for Mach number 0.6, 1 and 2.5 By RBF neural network

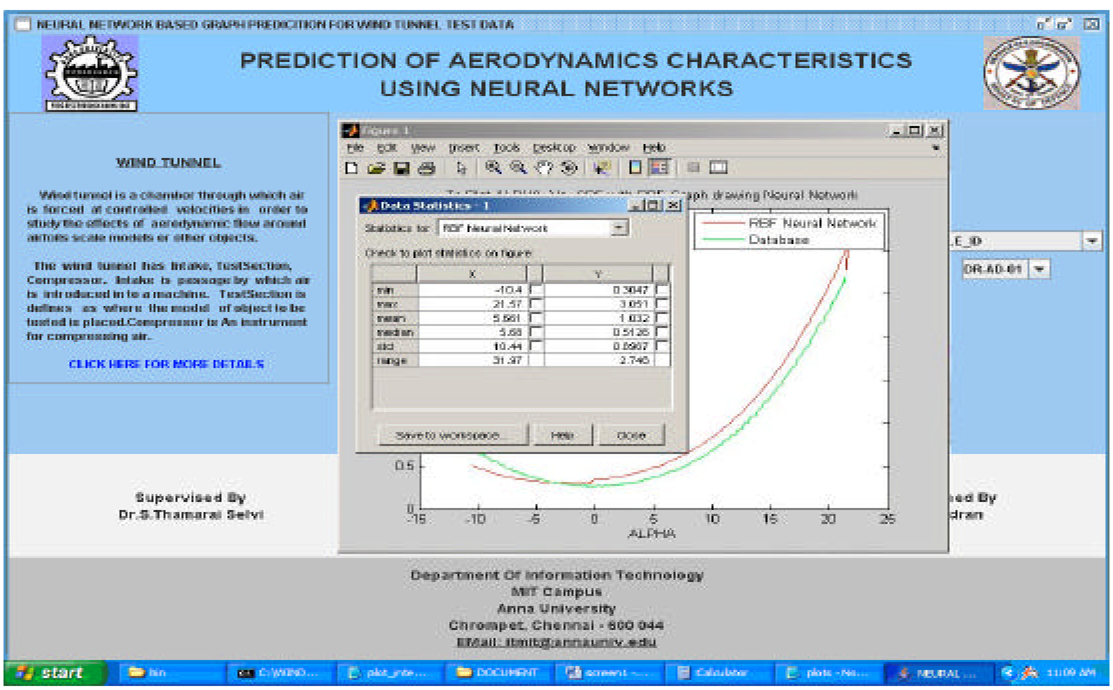

Fig. 8: Plot to show the comparison between graph predicted by neural network and graph drawn from database

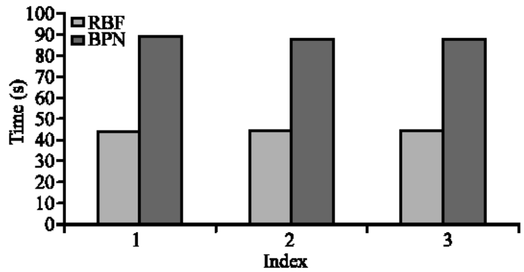

Fig. 9: Plot to show the time for convergence

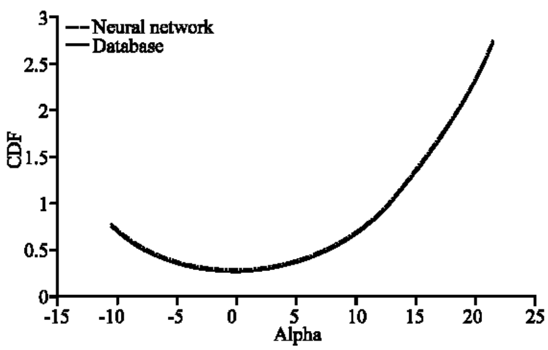

Fig. 10: Plot to show the sample graph drawn during the learning trial of BPN neural network (with rectification)

CONCLUSION

This study showed the applicability of the neural network approach to graph prediction in the wind tunnel test using the angle of attack and coefficient of frictional drag coefficients. The back propagation network performed similar to the Radial basis function neural network but the time factor involved with the backpropagation network is high. The back propagation neural network topology of 18,28,10,1 and systematically selected network parameters (learning rate of 0.35, no momentum factor and about 150 epochs), performed equally better with the radial basis function neural network in both recall and generalization. This study presents a complete neural network development process of training, recall and generalization for an interesting wind tunnel test application. The research provides fruitful results to make neural network computing more suitable to draw new graphs in wind tunnel tests with any mach number.

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