Knowledge-Based Aerodynamic Estimation of Airships

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***Abstract*—High fidelity flight modeling and simulation generally involves development of mathematical models based on aerodynamics and flight characteristics derived from experimental or numerical data. The data is generally recorded in look-up tables and called in during simulation. This results in very high computational cost (time & hardware requirements). An alternative, discussed in this paper, is to use a computational and knowledge-based paradigm, called neural networks. The network is presented with the experimental data and learns the relationships between forces and moments in six degrees of freedom. This modeling strategy has important implications for modeling the behavior of novel and complex flying configurations, such as airships that are considered in this paper. The pipeline includes, digitization of wind tunnel data, compatibility of digitized data with neural network (feed-forward) followed by development of six degree of freedom aerodynamic model. The preliminary results of using neural networks to model aerodynamic forces & moments look promising.**

***Index Terms*—Artificial Neural Networks (ANN), artificial intelligence, airships, wind tunnel testing, flight dynamics, aerodynamic estimation**

I. Introduction

Airship demonstrated the first controlled flight by any aerial vehicle. It is a lighter than air aircraft which navigate through air by means of propulsive power. Interests in airship technology again took a high after the 1970’s oil crisis. Major international institutes conducted number of studies in airship technology due to its low fuel consumption. In 1987, Gomes *et al*. [1] YEZ-2A project airship was designed. Extensive wind tunnel testing was carried out to obtain aerodynamic data for the airship which was then used for computer simulation of airship aerodynamics. Wind tunnel results were verified from flight test data of existing airships. Simulation language

Advanced Computer Simulation Language (ACSL) was used for non linear modeling. YEZ-2A aerodynamics were studied using said computer simulation model. Results obtained from extensive wind tunnel testing are in the form of discrete sets. Gomes used these results for simulation of airships flight dynamics.

Curve fitting capacity of artificial neural networks (ANN) has been utilized by many researchers in the past [2]-[4] to construct continuous output which can then interpolate and extrapolate with considerable accuracy. However, this capability of ANN was not used previously for wind tunnel test results. Mazhar *et al*. [5] successfully used curve fitting capability of ANN to generate approximate pressure functions in terms of coordinates. Comparison between ANN results and higher order polynomial based 2D curve fitting was drawn. ANN gave 10 times more accuracy in terms of mean square error.

Literature review of airship aerodynamics simulations revealed that many different approaches were used for this purpose but ANN modeling was not adopted during any research. However, literature review in the field of ANN clearly suggest that this approach can be beneficial in term of aerodynamic modeling. The potential of ANN in the fields of engineering and artificial intelligence has also been explored by number of researchers. Similarly, the field of aerospace is not an exception. Techniques covering the application of neural networks alone or in combination with other techniques have been utilized earlier to solve a range of problems. Bucar *et al*. [6], [7] implemented neural networks based model to envisage metal fatigue life by S-N curve scatter prediction. Numerical dependence of fatigue on maximum stress amplitude, notch factor, and temperature and stress ratio

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was investigated. Capability of ANN to predict key material properties of steel accurately was demonstrated by Sterjovski *et al.* [8]. Predictive model yielded quite healthy accuracy.

Composites possessing non-linear material properties pose a real challenge in terms of strength and reliability assessment. Lopes *et al*. [9] addressed the said deficiency by developing an ANN based reliability analysis model of composite materials as an alternative to conventional approach. The work aimed to decrease the overall computational time. Reliability based constrained composite strength optimization was done by Gomes *et al*. [10] through ANN and Genetic Algorithms (GA). A laminated composite shell was optimized to find the best ply orientation for a given reliability index. A hybrid intelligent system was proposed by Zheng *et al*. [11] through integrating ANN, genetic algorithm and fuzzy logic for training radial basis network. In the field of design optimization, Huskenet *et al*. [12] investigated different neural network models in fitness approximation for optimum design. Two different types of algorithms based upon approximation error with respect to available data and the learning ability of the networks to different problems with high accuracy and speed were used to investigate their effect on optimization.

Polynomial fitting and approximation to capture non-linearity in data using multilayer feed-forward ANN was explored by Pei *et al*. [13]. He used higher order terms in Taylor series expansion of sigmoid function to elaborate the correlation between power of polynomial and the number of neurons in hidden layer. Bishop *et al*. [14] proposed the application of ANN using multilayer perceptrons for fast curve fitting to map experimental data. Xueming *et al*. [15] successfully used neural networks in a reverse engineering problem to generate 3D surface profile. Saleem [16] employed a third degree polynomial fitting technique to approximate the pressure and temperature data on the turbine blade with an overall mean error below five percent for temperature and 10 percent for pressure distribution. Fruthwirth *et al*. [17] presented the application of ANN in hydraulic pressure prediction in drilling. Chen *et al*. [18] devised ANN based technique to predict the pressure coefficient for roof of low buildings. Training of model was done from wind tunnel experimental data. Uematsua *et al*. [19] used wind tunnel data, along with a time-series simulation technique, issued to train neural network to develop a computer based load evaluation system for calculating pressure coefficients using geometric and aerodynamic information. Kulkarni *et al*. [20] proposed a methodology to predict wind speed employing neural networks and statistical techniques.

The potential of ANN in the field of aerospace technology has also been recognized. Faller *et al*. [21] presented potential applications of ANN to meet the current and future technological needs in aeronautics. Capability to handle extremely complex unsteady and non-linear flight dynamics models was presented. ANN can also find applications in real time active control systems, flight simulation and aircraft health monitoring / fault identifications.

Structural failure mechanism of aerospace components during the accidents was simulated by Lanzi *et al*. [22]. A comparison between finite element analysis and ANN was presented in the paper, which concluded that neural networks are capable of producing simple and fast crashworthiness approximation.

Application of artificial intelligence in aircraft design is an emerging field. Oroumieh *et al*. [23] presented a scheme for employing artificial intelligence in preliminary aircraft design to reduce the design cycle time. Two artificial intelligence techniques namely, fuzzy logic and ANN have been utilized. Likewise, in another application Patniak *et al*. [24] reported application of ANN along with regression approximation to improve a flight optimization code; thereby reducing the calculation time significantly. Carn *et al*. [25] successfully employed ANN to predict aircraft aerodynamic loads during flight using aircraft flight data.

Kumar *et al.* [26] performed system identification for a rotorcraft employing ANN to estimate aerodynamic stability and control derivatives. Radial basis function neural networks are trained using simulation data from the coupled equations of motion of the vehicle. Rai and Madavan *et al*. [27] used a simple two-layer feed-forward network to design 2D airfoils for turbo-machinery. Jahangirian and Shahrokhi *et al*. [28] employed a multilayer perceptron neural network along with genetic algorithm for aerodynamic shape optimization of transonic airfoils. Kharal and Saleem *et al*. [29] presented an ANN based technique to generate an airfoil for given pressure coefficient values. Bezier–Parsec Parameterization technique was used for parameterization of airfoil geometry.

Utilization of ANN techniques to predict the flight dynamics is area which has yet not been explored to its potential. Likewise, ANN has yet not seen an application in the field of airships. Therefore, considering the computational powers of this technique, same will be applied to develop airship aerodynamics predictive model.

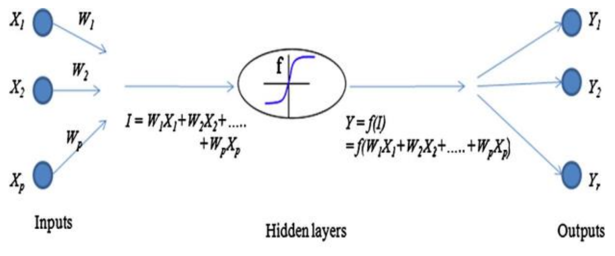

Figure 1. Artificial neural network model

II. Artificial Neural Networks

ANN consists of number of interconnected elements which work together with a processing system just like brain to compute values from inputs. These elements are called artificial neurons. The network is capable of performing extremely large computations for data processing [30], [31]. Neural network can change their structure mathematically on the basis of external inputs during the learning phase [32]-[34]. To achieve desired or target output, the neural network model is trained by adjusting weights to different inputs and biases to different layers till the time considerable amount of matching is achieved between model output and target output. ANN model is usually a layered structure having three layers i.e. input layer, hidden layer and output layer [35]. Structure of an artificial neural network model is shown below in the Fig. 1.

In ANN, the input layer receives all the inputs. Then in hidden layer, all the inputs are multiplied by weights to adjust the remaining error. Transfer function also known as activation function shown before output layer uses predefined logic to calculate the output. Working of single neuron in a neural network model can be mathematically written as:

$$N_i = X_i * W_{ii} + B_i \tag{1}$$

$$Y_i = f\,(X_i * W_{ii} + B_i) \tag{2}$$

where N_i is the first neuron, X_i is input, W_{ii} is weight allocated to first input, B_i is the bias added to first layer, Y_i is output and f is the transfer function. Transfer function converts the inputs in output as per predefined logic. Some commonly used transfer functions are shown below in Table I.

TABLE I. TRANSFER FUNCTIONS

Transfer Function	Value	Output range
Log Sigmoid	$f(x) = 1/(1 + e^{-x})$	0, 1
Tan Sigmoid	$f(x) = (e^{x} - e^{-x}) / (e^{x} + e^{-x})$	-1, 1
Hard Limit	$f(x) = \{0$, if $x < 0$ or 1 if $x \geq 1\}$	0 or 1

The objective of this research is development of six degree of freedom aerodynamic model of airship. Several studies have frequently used aerodynamic estimations in aerodynamics[36]-[39], flight performance [40], flight dynamics[41]-[43] and aircraft control [44] applications. ANN technique serves as alternative approach for accurate modeling in very less time frame. A highly accurate predictive model of airship is made by utilizing MATLAB® neural network module. Initially the wind tunnel data of airship is analyzed to establish the input and output parameters. The digitized data is refined by reducing the noise level. Then the data would be sorted in a way that it can be used in neural network module of MATLAB® necessary for supervised training of the network. Number of input and output parameters are standardized in accordance with target requirements. After training and optimizing network, final optimized neural network model is developed. Supervised training involves training of neural network to produce output with maximum possible accuracy to wind tunnel results of airship. The output aerodynamic coefficient are coefficient of lift, drag, side force, pitching moment, rolling moment and yawing moment.

A. Problem Formulation & Description

ANN module requires information in a digitized format. Digitization of data is process in which data is converted into digital format. Information is organized in discrete units in this format and is known as bits. This is a binary data and can be processed by computers or any computerized equipment accordingly as per its computational ability.

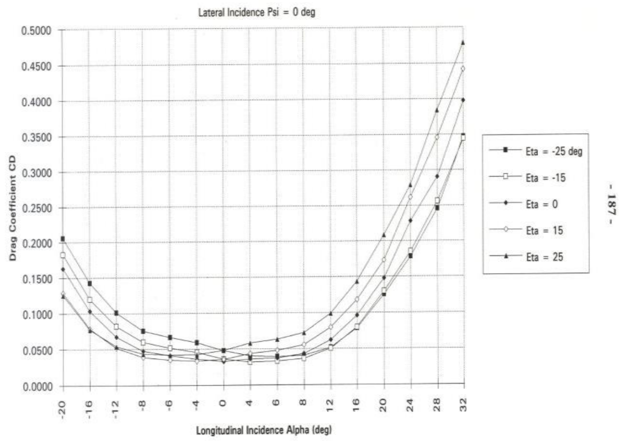

Figure 2. Aerodynamic data for coefficient of drag expressed as a function of angle of attack, roll angle and elevator deflection angle

CurveSnap® tool is used to digitize all the graphs of aerodynamic data. As an example, the graph shown in Fig 2 contains information of response of airship to elevator movement in a wind tunnel. With inputs of longitudinal incidence (deg) -20 to 32, lateral incidence (deg) 0, elevator deflection (deg) -25,-15,0,15,25 output graphs of Coefficient of Drag (CD) are plotted. The traced data points are copied and exported to spread sheet for simple interfacing with MATLAB® ANN toolbox. The aerodynamic data is a function of five inputs; longitudinal incidence angle, lateral incidence angle, flaps deflection, aileron deflection and rudder deflection. The six output aerodynamic coefficients are lift, drag, side force, pitching moment, rolling moment and yawing moment.

Weighted inputs along with biases of all neurons in a layer are fed to the transfer function for activation of the neuron. The selection of the transfer function for a particular layer depends on the type of data and the specific range that is required for the output. Tan sigmoid transfer function is used in the hidden layer and pure linear in the output layer (Fig. 3).

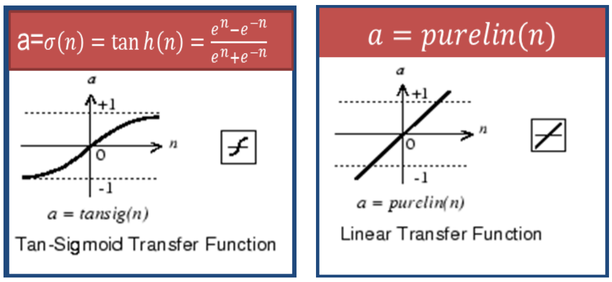

Figure 3. Tan-Sigmoid and linear transfer function

The inputs to this work are concurrent, non-sequential and therefore not time barred. The required output is also not a time series but a pure prediction problem, therefore feed forward static neural network is used. A two layered feed forward network with five inputs, having a single hidden layer with 10 neurons as an initial guess and 1 neuron in output layer is created. The transfer functions are tan sigmoid in hidden layer and pure linear in output layer as shown in Fig. 4.

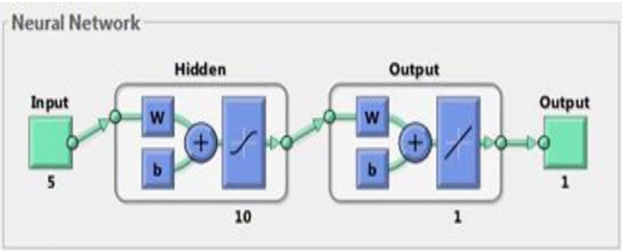

Figure 4. Two layered feed forward network

Before training the network, data is divided into three parts. These three sets are training, validation and testing sets. Training set is used for adjustment of weights and biases to compute the gradient. Validation set tunes network parameters other than weights and its error is analysed during the training process. Increasing error on the validation set accounts for the over fitting of the data. Test set is not used during training; it only tells how well the network generalizes on new data [45].

After initialization, adjustment of weights and biases is carried out iteratively. Training is the basic process in which an initialized network learns to generate required results after undergoing learning by presentation of inputs and outputs. *Supervised learning* would be used where the network would be provided with the targets to compare with the network outputs and adjust the weights accordingly. The training style used would be *batch training* where the weights and bias would be updated once all the data set has gone through the network.

During training, performance function of network is minimized. The performance function selected for this work is Mean Square Error (MSE) between outputs and targets. Gradient of MSE is used for adjustment of weights to minimize error function.

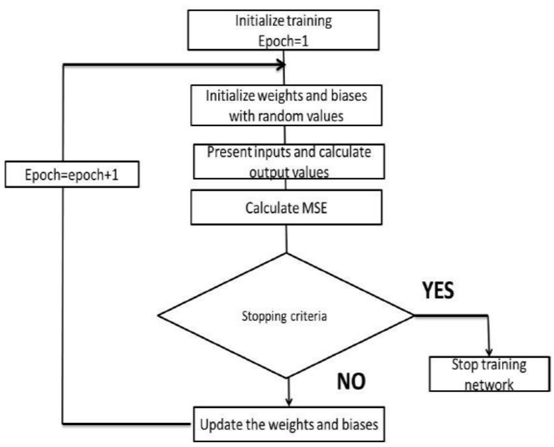

Figure 5. Flowchart for back propagation algorithm

The technique deployed to determine the gradient is called back propagation. Back propagation algorithm computes gradients and Jacobian of the network error with respect to weights as shown in Fig. 5. The Levenberg Marquardt algorithm is a numerical method designed to improve the standard back propagation. It is an iterative method and has adequate performance on fitting problems. It is employed as the initial training function for the networks to be modeled.

Six networks are modeled in order to establish a final model able to predict aerodynamic forces and moments acting on the airship. However, initially a two layered feed forward back propagation network will be made predicting only one output that is coefficient of drag. The associated results are discussed next.

III. Implementation and Discussion

With ten neurons in hidden layer and using Levenberg-Marquardt training algorithm, results are analysed with following data divisions:

- 70% - training, 15% - validation, 15% - testing
- 60% - training, 20% - validation, 20% - testing
- 80% - training, 10% - validation, 10% - testing

Fig. 6 shows the MSE reduction of training, validation and testing against iterations. It can be seen that the error is continuously reducing and correspondingly the validation error is also reducing. However using the early stopping criterion once the error in validation data set increases for 6 consecutive iterations the training is stopped and the network weights and bias are fixed. The results shown are for data division of 70% training, 15% validation and 15% testing.

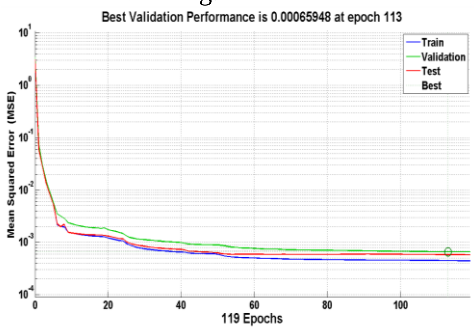

Figure 6. Performance (70% for training, 15% for validation and 15% for testing)

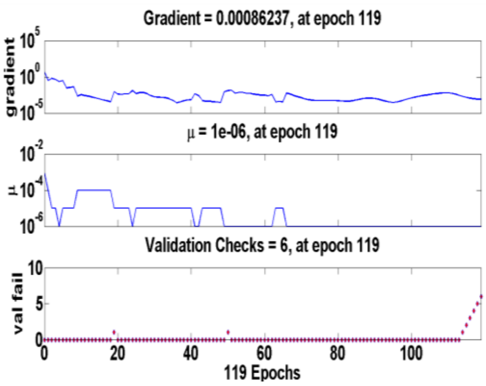

Figure 7. Training State (70% for training, 15% for validation and 15% for testing)

Fig. 7 shows the state of training. Failure of validation check, gradient and step size are shown against each iteration. Fig. 8 shows the error histogram for all the data sets. It can be clearly seen that the network has been trained ideally and the error distribution is a near perfect normal distribution from the mean. This shows that the network behavior is almost the same on all data sets and shows that the network has a very good generalization ability and its predictions would be very accurate.

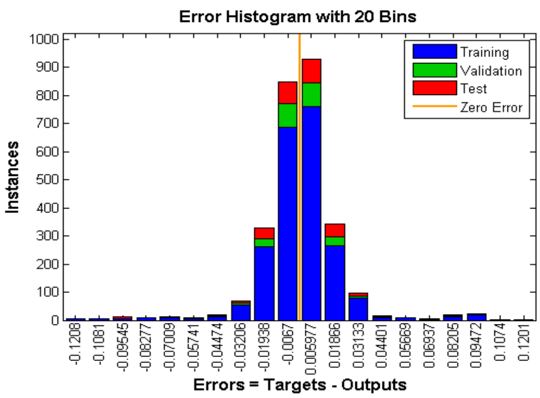

Figure 8. Error Histogram (70% for training, 15% for validation and 15% for testing)

Fig. 9 shows the regression between the targets and network outputs in the three data sets individually and then as a whole for the complete data set. Perfect relation or fit will result in slope of 1. The regression values are very close to perfect fit showing a very strong relation.

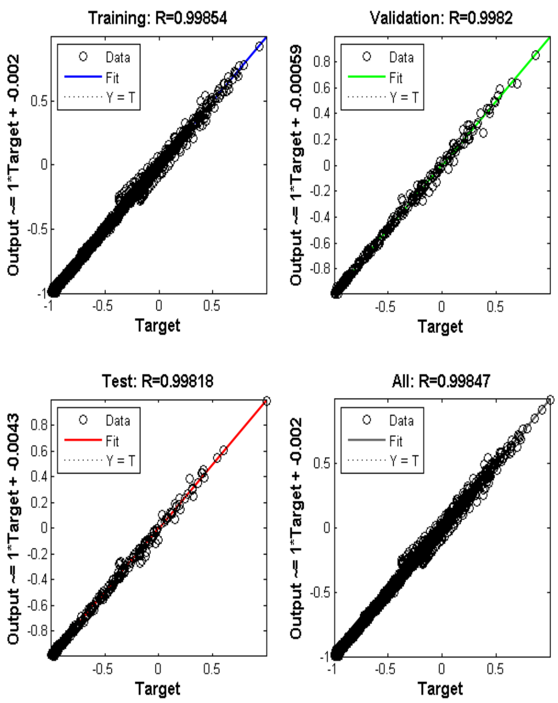

Figure 9. Regression Analysis (70% for training, 15% for validation and 15% for testing)

TABLE II. Effect of Change of Data Division

Data Division	Slope	Correlation Coefficient	Mean Square Error
80%,10%,10%	0.9952	0.9971	9.089e-04
60%,20%,20%	0.9946	0.9971	9.118e-04
70%,15%,15%	0.9923	0.9965	0.0011

The analysis suggest distributing 80% data for training, 10% for validation and 10% for testing would result in best generalization of network as shown in Table II. As this division yielded best regression **R** (correlation coefficient) between network outputs and corresponding targets and least mean square error.

A. Effect of Number of Neurons

Effect of change in number of neurons in hidden layer are also analysed. Best data division has already been selected that is 80% training, 10% validation and 10% testing. Above explained three parameters will be calculated by changing number of neurons. Effect of change in number of neurons on slope of best linear regression, correlation coefficient and mean square error is appended below:

TABLE III. Effect of Change in Numberof Neurons

Neurons	Slope	Correlation Coefficient	MSE
10	0.9952	0.997	9.089e-04
15	0.9964	0.99799	6.31406e-04
20	0.9971	0.9984	5.0332e-04
22	0.9966	0.99847	4.8211e-04
25	0.9968	0.9984	4.9354e-04
30	0.9952	0.9971	9.089e-04

From above mentioned Table III, it is affirmed that best results are obtained with keeping number of neurons 22 in hidden layer.

B. Effect of Training Algorithm

Training algorithm being most important element of a network greatly affect the performance of a network. Effects of change in algorithm on network are appended in Table IV. It can be seen that Levenberg-Marquardt training algorithm yields best results.

TABLE IV. Effect with Change in Training Algorithm

Algorithm	Slope	Correlation Coefficient	Mean Square Error
Levenberg-Marquardt	0.9966	0.9984	4.821e-04
One step secant	0.9627	0.9824	0.0055
Scaled conjugate gradient	0.9804	0.9912	0.0027
BFGS Quasi-Newton	0.9837	0.9926	0.00232
Gradient descent	0.8023	0.8184	0.0561
Resilient (RPROP)	0.9672	0.9854	0.0046

IV. Summary

We have presented ANN based technique that develops computationally cheaper mathematical model of flight dynamics of Airships. The main benefits in using a neural network approach are that all flight characteristics can be represented within a unified environment of a neural network and that the network is built directly from experimental data using the self organizing capabilities of the neural network. The network is presented with the experimental data and learns the relationships between forces and moments in six degrees of freedom. A highly accurate predictive model of airship is made utilizing MATLAB® neural network module. The results of using neural networks to model aerodynamic forces & moments are very promising.

References

[1] S. B. V. Gomes, “An investigation of the Flight Dynamics of Airships with the application to the YEZ-2A,” PhD. thesis, Cranfield Institute of Technology, 1990.

[2] Z. H. Khan, T. S. Alin, and M. A. Hussain, “Price prediction of share market using artificial neural network (ANN),” *International Journal of Computer Applications*, vol. 22, no. 2, pp. 42-47, 2011.

[3] V. Pacelli, V. Bevilacqua, and M. Azzollini, “An artificial neural network model to forecast exchange rates,” *Journal of Intelligent Learning Systems and Applications*, vol. 3, no. 2, pp. 57, 2011.

[4] A. Mellit, S. Sağlam, and S. A. Kalogirou, “Artificial neural network-based model for estimating the produced power of a photovoltaic module,” *Renewable Energy*, vol. 60, pp. 71-78, 2013.

[5] F. Mazhar, A. M. Khan, I. A. Chaudhry, and M. Ahsan, “On using neural networks in UAV structural design for CFD data fitting and classification,” *Aerospace Science and Technology*, vol. 30, no. 1, pp. 210-225, 2013.

[6] T. Bucar, M. Nagode, and M. Fajdiga, “A neural network approach to describing the scatter of S-N curves,” *International Journal of Fatigue*, vol. 28, pp. 311-323, 2006.

[7] T. Bucar, M. Nagode, and M. Fajdiga, “An improved neural computing method for describing the scatter of S-N curves,” *International Journal of Fatigue*, vol. 29, pp. 2125-2137, 2007.

[8] Z. Sterjovski, D. Nolan, K. R. Carpenter, D. P. Dunne, and J. Norrish, “Artificial neural networks for modeling the mechanical properties of steels in various applications,” *Journal of Materials Processing Technology*, vol. 170, pp. 536-544, 2005.

[9] P. A. M. Lopes, H. M. Gomes, and A. M. Awruch, “Reliability analysis of laminated composite structures using finite elements and neural networks,” *Composite Structures*, vol. 92, pp. 1603-1613, 2010.

[10] H. M. Gomes, A. M. Awruch, and P. A. M. Lopes, “Reliability based optimization of laminated composite structures using genetic algorithms and artificial neural networks,” *Structural Safety*, vol. 33, pp. 186-195, 2011.

[11] S. Zheng, Z. Li, and H. Wang, “A genetic fuzzy radial basis function neural network for structural health monitoring of composite laminated beams,” *Expert Systems with Application*, vol. 38, pp. 11837-11842, 2011.

[12] M. Husken, Y. Jin, and B. Sendhoff, “Structure optimization of neural networks for evolutionary design optimization,” *Soft Computing*, vol. 9, pp. 21-28, 2005.

[13] J. Pei, J. P. Wright, and A. W. Smyth, “Mapping polynomial fitting into feedforward neural networks for modeling nonlinear dynamic systems and beyond,” *Computer Methods in Applied Mechanics and Engineering*, vol. 194, pp. 4481-4505, 2005.

[14] C. M. Bishop and C. M. Roach, “Fast curve fitting using neural networks,” *Review of Scientific Instruments*, vol. 63, no. 10, pp. 4450-4456, October 1992.

[15] H. Xueming, L. Chenggang, H. Yujin, Z. Rong, S. X. Yang, and G. S. Mittal, “Automatic sequence of 3D point data for surface fitting using neural networks,” *Computers & Industrial Engineering*, vol. 57, pp. 408-418, 2009.

[16] S. Saleem, “Static and dynamic analysis of centrifugal compressor impeller of a small turbo fan engine using finite element method,” MS thesis, Dept. of Aerospace Engg., CAE, National University of Sciences & Technology, Risalpur, Pakistan, 2007.

[17] R. K. Fruhwirth, G. Thonhauser, and W. Mathis, “Hybrid simulation using neural networks to predict drilling hydraulics in real time,” in *Proc. SPE Annual Technical Conference and Exhibition*, Society of Petroleum Engineers..

[18] Y. Chen, G. A. Kopp, and D. Surry, “Prediction of pressure coefficients on roofs of low buildings using artificial neural networks,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 91, pp. 423-441, 2003.

[19] Y. Uematsua and R. Tsuruishi, “Wind load evaluation system for the of roof cladding of spherical domes,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 96, pp. 2054-2066, 2003.

[20] M. A. Kulkarni, S. Patil, G. V. Rama, and P. N. sen, “Wind speed prediction using statistical regression and neural network,” *Journal of Earth System Science*, vol. 177, no. 4, pp. 457-463, August 2008.

[21] W. E. Faller and S. J. Schreck, “Neural networks: applications and opportunities in aeronautics,” *Progress in Aerospace Science*, vol. 32, pp. 433-456, 1996.

[22] L. Lanzi, C. Bisagni, and S. Ricci, “Neural network systems to reproduce crash behavior of structural components,” *Computers & Structures*, vol. 82, pp. 93-108, 2004.

[23] M. A. A. Oroumieh, S. M. B. Malaek, M. Ashrafizaadeh, and S. M. Taheri, “Aircraft design cycle time reduction using artificial intelligence,” *Aerospace Science and Technology*, vol. 26, pp. 244-258, 2013.

[24] S. N. Patnaik, R. M. Coroneos, J. D. Guptill, D. A. Hopkins, and W. J. Haller, “A subsonic aircraft design optimization with neural network and regression approximators,” in *Proc. 10th Multidisciplinary Analysis and Optimization Conference*, Albany, New York, Aug. 30-Sep. 1, 2004.

[25] C. Carn, “The inverse determination of aircraft loading using artificial neural network analysis of structural response data with statistical methods, PhD. dissertation, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University, Melbourne, Australia, 2005.

[26] R. Kumar, R. Ganguli, and S. N. Omkar, “Rotorcraft parameter estimation using radial basis function neural network,” *Applied Mathematics and Computatio*n, vol. 216, pp. 584-597, 2010.

[27] M. M. Rai and N. K. Madavan, “Application of artificial neural networks to the design of turbomachinery airfoils,” *Journal of Propulsion and Power*, vol. 17, no. 1, 2001.

[28] A. Jahangirian and A. Shahrokhi, “Aerodynamic shape optimization using efficient evolutionary algorithms and unstructured CFD solver,” *Computers & Fluids*, vol. 46, pp. 270-276, 2011.

[29] A. Kharal and A. Saleem, “Neural networks based airfoil generation for a given Cp using Bezier-PARSEC parameterization,” *Aerospace Science and Technology*, vol. 23, pp. 330-344, 2012.

[30] R. Hecht-Nielsen, *1990-Neurocomputing*, Addison-Wesley, Reading, MA, 1990.

[31] R. J. Schalkoff, *1997-Artificial Neural Networks*, McGraw-Hill, New York, 1997.

[32] Artificial neural network, Wikipedia. [Online]. Available: http://en.wikipedia.org/wiki/Artificial_neural_network

[33] M. T. Hagan, H. B. Demuth, M. Beale, *Neural Network Design*, PWS Publishing Company, USA.

[34] C. Stergou and D. Sigano. Neural networks. [Online]. Available: http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html

[35] S. Haykin, *Neural Networks: A Comprehensive Foundation*, Prentice Hall, NJ, USA.

[36] A. Maqsood and T. H. Go, “Optimization of hover-to-cruise transition manuever using variable incidence wing,” *Journal of Aircraft*, vol. 47, no. 3, pp. 1060-1064, 2010.

[37] A. Maqsood and T. H. Go, “Optimization of transition maneuvers through aerodynamic vectoring,” *Aerospace Science and Technology*, vol. 23, no. 1, pp. 363-371, 2012.

[38] A. Maqsood and T. H. Go, “Aerodynamic characteristics of a flexible membrane micro air vehicle,” *Aircraft Engineering & Aerospace Technology*, vol. 87, no. 1, pp. 30-37, 2015.

[39] A. Maqsood and T. H. Go, "Lift estimation of low aspect ratio wings based on suction analogy," *AIAA Journal*, vol. 51, no. 2, pp. 529-534, 2013.

[40] A. Maqsood and T. H. Go, "Parametric studies and performance analysis of a biplane micro air vehicle," *International Journal of Aeronautical and Space Sciences*, vol. 14, no. 3, pp. 229-236, 2013.

[41] A. Maqsood and T. H. Go, "Longitudinal flight dynamic analysis of an agile UAV," *Aircraft Engineering and Aerospace Technology*, vol. 82, no. 5, pp. 288-295, 2010.

[42] A. Maqsood and T. H. Go, "Multiple time scales analysis of aircraft longitudinal dynamics with aerodynamic vectoring," Nonlinear Dynamics, vol. 69, no. 3, pp. 731-742, 2012.

[43] T. H. Go and A. Maqsood, "Effect of aspect ratio on wing rock at low reynolds number," *Aerospace Science and Technology*, vol. 42, pp. 267-273, 2015.

[44] A. Maqsood and T. H. Go, "Optimal transition maneuver stability and control using aerodynamic vectoring," in *Proc. 50th AIAA Aerospace Sciences Meeting and Exhibit*, 2012, p. 855.

[45] H. Demuth, M. Beale, and M. Hagan, *Neural Network Toolbox™ 6*, User Guide, vol. 2008, 1992.

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