Aerodynamic Database Improvement of Aircraft based on Neural Networks and Genetic Algorithms

Conference Paper · July 2017

DOI: 10.13009/EUCASS2017-226

Murat Canıbek
TAI - Turkish Aerospace Industries, Inc.

DOI: 10.13009/EUCASS2017-226

Aerodynamic Database Improvement of Aircraft based on Neural Networks and Genetic Algorithms

Fazil Selcuk Gomec and Murat Canibek
Aerodynamics, Modelling & Control Dept., Aircraft Group, Turkish Aerospace Industries Inc. (TAI)
Ankara 06980, Turkey

Abstract
Aerodynamic database of an aircraft is created with combinations of analytical and empirical methods, CFD analyses, wind tunnel tests and flight tests. The database is required to evaluate aircraft's stability and control characteristics, flight performance and handling qualities. In current case, only Navier-Stokes based CFD analyses are used in the database. To cover all database item CFD analyses may take several months. In this paper, performance of a neural network model optimized by a genetic algorithm is investigated to decrease the computational time and increase the number of considered flight conditions.

1. Introduction

Aerodynamic database generation is required for stability, control and performance analyses of an aircraft. It is composed of static coefficients, static and dynamic derivatives. These coefficients and derivatives are functions of aircraft flight conditions, control surface deflections, flaps, landing gears, speed brakes and other moving surfaces. Therefore, the database is created by investigating a lot of combinations of them. These can be achieved by different computational or experimental methods depending upon the required accuracy. The well-known ones of these methods are wind tunnel tests, flight tests and computational models including CFD, DATCOM, ESDU etc. [1]. While the re-entry aerodynamics of a solid rocket booster after the separation can be obtained by wind tunnel tests, the separation characteristics of it can be computed by an inviscid CFD approach, [2] [3] [4]. Also, the effect of a dorsal fin at high side slip angles can be modelled by RANS CFD approaches [5]. Although CFD techniques are well known approaches to calculate static coefficients, they can also be utilized to compute static and dynamic derivatives [6].

To simulate all flight conditions and aircraft configurations in the aerodynamic database require an excessive time for CFD analyses, wind tunnel tests or flight tests. More than a thousand analyses or tests should be done for accurate results. Therefore, a surrogate model should be used to cover a portion of the database instead of analyzing or testing all points. Response surface models, Kriging algorithm and artificial neural networks are the main types of surrogate models [7].

Artificial neural networks are learning algorithms and composed of layers including artificial neurons. Each neuron has been interconnected to other neurons dependent upon the network structure. The interconnections are modelled with input weights, neuron activation functions and neuron biases. The biases and input weights are computed in a learning process with training inputs.

Aerodynamic coefficients of an airfoil or aircraft can be computed with the collaboration of flow solvers and neural networks [8]. Also, the shape optimization of rotor blades, high speed trains, tall buildings can be done with the help of artificial neural networks and a genetic algorithm approach [9] [10] [11].

The most common neural network models in the literature are the multilayer perceptron (MLP), functional link (FLN) and radial basis function (RBF) networks [8]. Taylor and Fourier series are primitive examples for artificial neural networks [12].

In the present study, performance of an MLP neural network model optimized by a genetic algorithm is investigated to decrease the computational time for aerodynamic database generations and to improve a present database. The aerodynamic database in this study includes static coefficients and control surface hinge moments of a generic aircraft. A Reynolds averaged Navier-Stokes(RANS) flow solver is used for CFD analyses to obtain aerodynamic parameters.

DOI: 10.13009/EUCASS2017-226

2. Nomenclature

MAC : Mean Aerodynamic Chord
CFD : Computational Fluid Dynamics
CD : Drag Coefficient
CL : Lift Coefficient
CY : Side Force Coefficient
CR : Roll Moment Coefficient
CM : Pitch Moment Coefficient
CN : Yaw Moment Coefficient
CHMAL: Hinge Moment Coefficient of Left Aileron
CHMEL: Hinge Moment Coefficient of Left Elevator
CHMR : Hinge Moment Coefficient of Rudder
t : Target Value
d_m : Neural Network Output

3. Aerodynamic Database of the Generic Aircraft

To test the performance of the proposed neural network model (NNGA), an aerodynamic database is needed. For this purpose, a generic aircraft was designed with its control surfaces. The different views of it are shown in Figure 1 and control surfaces are indicated with different colors.

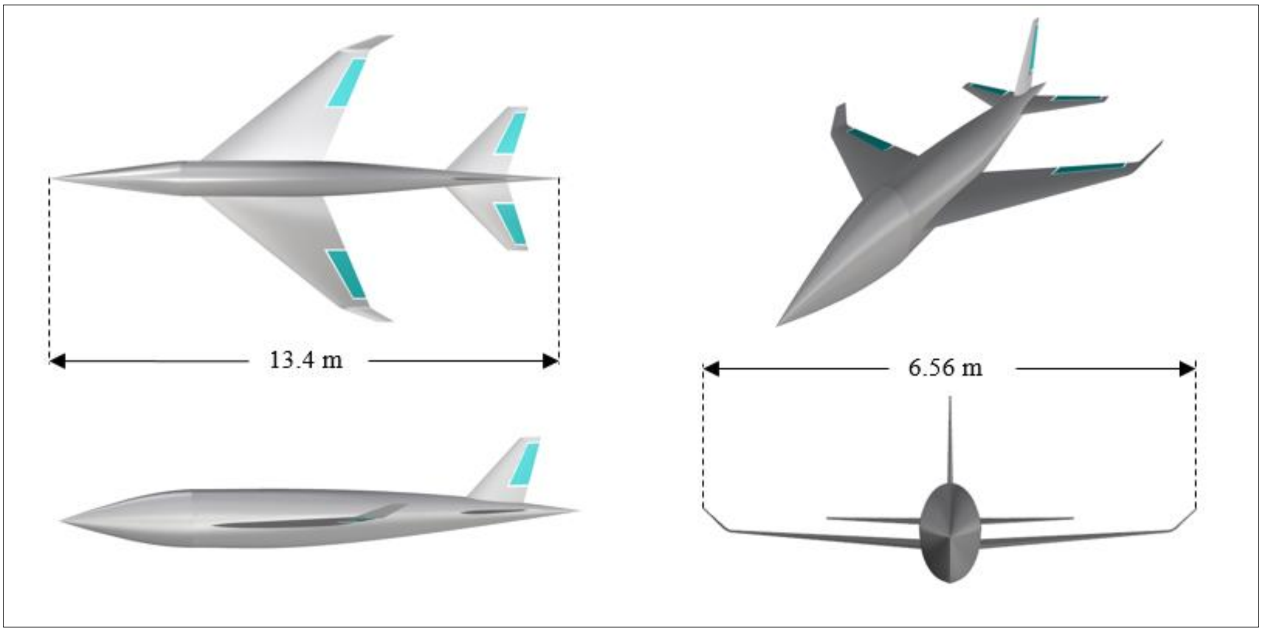


Figure 1. Top, side, front and perspective views of the generic aircraft

3080 points representing various flight conditions and aircraft configurations are selected. Static coefficients and control surface hinge moments of the designed aircraft are analyzed at 1628 points by a RANS flow solver. Remaining is not analyzed due to the possibility of derivations from symmetrical or identical flight conditions. For example; alfa sweep results of the rudder for the following conditions are identical.

- Rudder=20° & Beta=10° , Rudder=-20° & Beta=-10°

The reference area of the aircraft is 14.65 m^2. The reference chord length at MAC 25% is 2.503m and its span is 6.560 m. The aircraft database includes four sub-sections called as aileron deflected, baseline, elevator deflected and rudder deflected databases. While the baseline indicates the database of the clean configuration, others have control surface

DOI: 10.13009/EUCASS2017-226

deflections. The analyses points of these sections are shown in Table 1. Also, the numbers of CFD analyses and derived data from these analyses are shown in this table.

Table 1. Parameters of the Aircraft's Aerodynamic Database

<table>
<tr><td colspan="2" rowspan="2">AILERON DATABASE</td><td>Mach Number (4)</td><td>0.2, 0.4, 0.6, 0.8</td></tr>
<tr><td>Angle of Attack (°) (11)</td><td>-12,-9,-6,-3,0,3,6,9,12,15,18</td></tr>
<tr><td rowspan="2">Number of CFD Analyses</td><td rowspan="2">924</td><td>Side Slip Angle (°) (5)</td><td>-20,-10,0,10,20</td></tr>
<tr><td>Aileron Left/Right (°) (7)</td><td>-15/15,-10/10,-5/5,0,5/-5,10/-10,15/-15</td></tr>
<tr><td rowspan="2">Number of Derived Data</td><td rowspan="2">616</td><td>Elevator (°) (1)</td><td>0</td></tr>
<tr><td>Rudder (°) (1)</td><td>0</td></tr>
<tr><td colspan="2" rowspan="2">BASELINE DATABASE</td><td>Mach Number (4)</td><td>0.2, 0.4, 0.6, 0.8</td></tr>
<tr><td>Angle of Attack (°) (11)</td><td>-12,-9,-6,-3,0,3,6,9,12,15,18</td></tr>
<tr><td rowspan="2">Number of CFD Analyses</td><td rowspan="2">0</td><td>Side Slip Angle (°) (5)</td><td>-20,-10,0,10,20</td></tr>
<tr><td>Aileron Left/Right (°) (1)</td><td>0</td></tr>
<tr><td rowspan="2">Number of Derived Data</td><td rowspan="2">220</td><td>Elevator (°) (1)</td><td>0</td></tr>
<tr><td>Rudder (°) (1)</td><td>0</td></tr>
<tr><td colspan="2" rowspan="2">ELEVATOR DATABASE</td><td>Mach Number (4)</td><td>0.2, 0.4, 0.6, 0.8</td></tr>
<tr><td>Angle of Attack (°) (11)</td><td>-12,-9,-6,-3,0,3,6,9,12,15,18</td></tr>
<tr><td rowspan="2">Number of CFD Analyses</td><td rowspan="2">176</td><td>Side Slip Angle (°) (1)</td><td>0</td></tr>
<tr><td>Aileron Left/Right (°) (1)</td><td>0</td></tr>
<tr><td rowspan="2">Number of Derived Data</td><td rowspan="2">44</td><td>Elevator (°) (5)</td><td>-20,-10,0,10,20</td></tr>
<tr><td>Rudder (°) (1)</td><td>0</td></tr>
<tr><td colspan="2" rowspan="2">RUDDER DATABASE</td><td>Mach Number (4)</td><td>0.2, 0.4, 0.6, 0.8</td></tr>
<tr><td>Angle of Attack (°) (11)</td><td>-12,-9,-6,-3,0,3,6,9,12,15,18</td></tr>
<tr><td rowspan="2">Number of CFD Analyses</td><td rowspan="2">528</td><td>Side Slip Angle (°) (5)</td><td>-20,-10,0,10,20</td></tr>
<tr><td>Aileron Left/Right (°) (1)</td><td>0</td></tr>
<tr><td rowspan="2">Number of Derived Data</td><td rowspan="2">572</td><td>Elevator (°) (1)</td><td>0</td></tr>
<tr><td>Rudder (°) (5)</td><td>-20,-10,0,10,20</td></tr>
</table>

The database shown in Table 1 is used as training, test and validation inputs for NNGA. The percentage of each input and how this database can be created with smaller number of CFD analyses are discussed in this study. As seen in Table 1, the following parameters are used as input columns for neural network analyses.

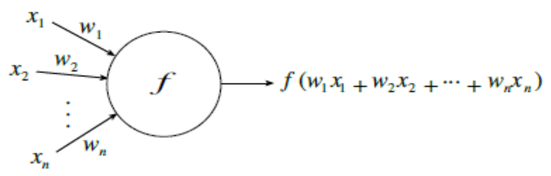
- Mach number
- Angle of attack
- Side slip angle
- Aileron deflection angle
- Elevator deflection angle
- Rudder deflection angle

The bolded datasets in this table are derived from other datasets computed by CFD analyses. In this study, how the number of CFD analyses can be decreased with a neural network model is focused. Therefore, only CFD based datasets are used in the neural network analyses.

DOI: 10.13009/EUCASS2017-226

4. Artificial Neural Networks Optimized with Genetic Algorithm (NNGA)

A feed forward neural network (MLP) with Levenberg-Marquardt backpropagation training algorithm is used in this study. It is composed of layers and these layers have artificial neurons which are interconnected to other neurons. A neuron and a neural network samples are shown in Figure 2.



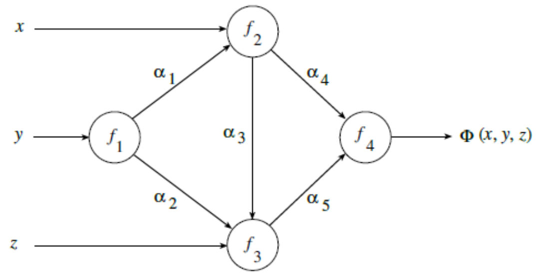


Figure 2. A neuron (left) and a neural network (right) models [12]

A four-layered network with two hidden layers is selected as layer architecture. An example of the network with hidden layers having 2 neurons is shown in Figure 3.

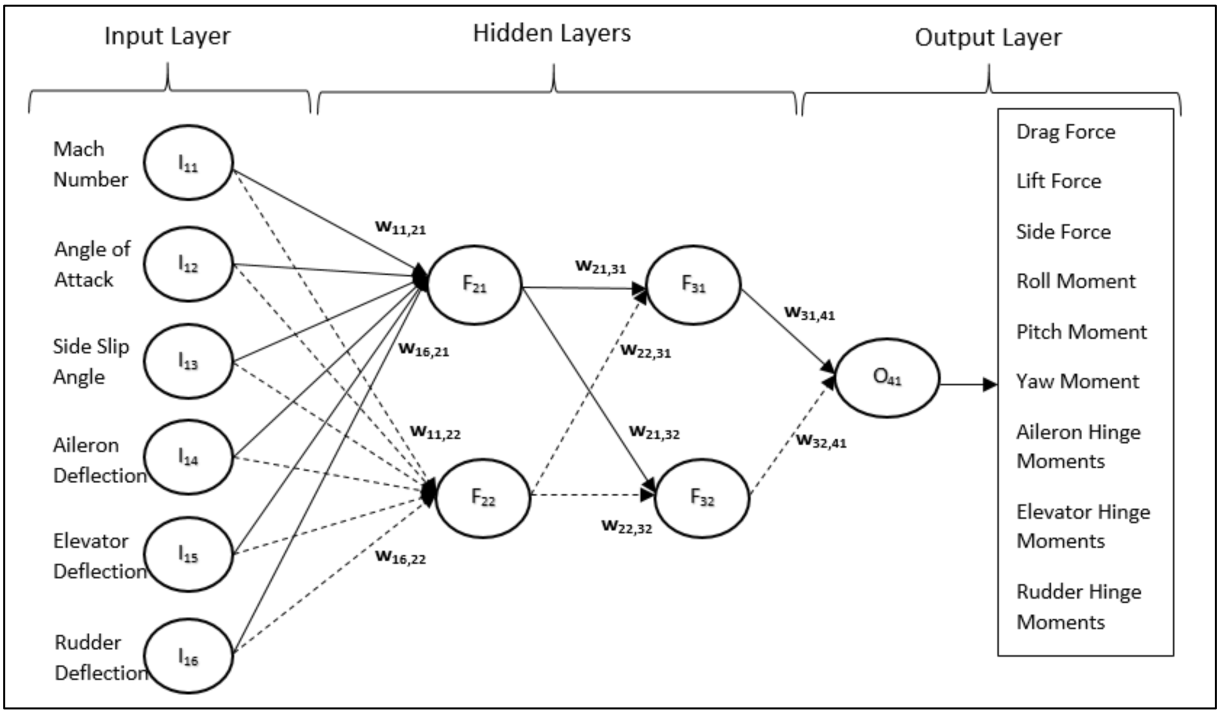


Figure 3. An example of the four layered network

As seen in Figure 3, six inputs affect the aerodynamic forces and moments. It is noted that each force and moment was calculated separately in this study. Feedforward formulation of network in Figure 3 is given in

DOI: 10.13009/EUCASS2017-226

Table 2. Feedforward formulations

$Y_{21} = F_{21}(\sum_{i=11}^{i=16} w_{i,21} I_i + b_{21})$	Log-Sigmoid Transfer Function $F_{21}(x) = \frac{1}{1+e^{-x}}$
$Y_{22} = F_{22}(\sum_{i=11}^{i=16} w_{i,22} I_i + b_{22})$	Log-Sigmoid Transfer Function $F_{22}(x) = \frac{1}{1+e^{-x}}$
$Y_{31} = F_{31}(Y_{21} w_{21,31} + Y_{22} w_{22,31} + b_{31})$	Pure-Linear Transfer Function $F_{21}(x) = x$
$Y_{32} = F_{32}(Y_{21} w_{21,32} + Y_{22} w_{22,32} + b_{32})$	Pure-Linear Transfer Function $F_{21}(x) = x$
$Y_{41} = O_{41}(Y_{31} w_{31,41} + Y_{32} w_{32,41} + b_{41})$	Pure-Linear Transfer Function $F_{21}(x) = x$

Determination of the number of neurons in hidden layers and initialization parameters are one of the most important aspects for neural network analyses. Initialization parameters are initial layer weights, biases and mu coefficient which is a part of backpropagation algorithm. In general, initial values of weights and biases are selected randomly. It causes different results for each independent run. Although it is a faster approach, it decreases accuracy and repeatability of the results. Therefore, the initial values should be chosen systematically. In this study, these values are computed for each layer by equally spacing between the selected upper and lower bounds. Initial weights of the input layer are selected as to be different from other layers. Also, the number of neurons in a hidden layer is user defined and constant parameter in the neural network method. To get the minimum error for the neural network analysis, the initial and the constant values are optimized by a genetic algorithm in this effort. Genetic algorithm and neural network functions of Matlab® are used in this study.

To summarize, the following parameters are optimized with the genetic algorithm.

- ✓ The number of neurons in hidden layers
- ✓ The lower and upper bound of initial hidden layer weight vectors
- ✓ The lower and upper bound of initial input layer weight vector
- ✓ The upper bound of bias vector
- ✓ The initial mu coefficient

In total, seven parameters of the artificial neural network are optimized. The genetic algorithm options used in the optimization step are listed in Table 3 [13].

Table 3. Genetic algorithm options

MigrationDirection	forward
PopulationSize	50
FitnessScalingFcn	@fitscalingtop
SelectionFcn	@selectiontournamet
EliteCount	5
CrossoverFraction	0.9

The optimized model is called as NNGA in this study. Although it needs more computational time, it is expected to obtain more accurate results than standard neural network models and polynomial curve fits. Nevertheless, the computational time of the neural network analysis can be thought as negligible compared to CFD analyses.

DOI: 10.13009/EUCASS2017-226

5. Model Validations

To validate NNGA, the aerodynamic database described in section 2 was used. A part of the database was chosen as the input database for the neural network analysis. Remaining part of the database was used to compare CFD and results of NNGA. Two different cases are focused in this paper for the validations of NNGA. In the first case, results of NNGA with respect to the validation datasets were compared with CFD analyses and 1st & 2nd order polynomial curve fits. In the second case, the validation datasets were chosen randomly from CFD based datasets given in Table 1. The details of them are described in this section.

An input database is required to update the weights and biases of a neural network. The network weights and biases are updated to minimize the error between the network output and training dataset. However, a lot of possibilities that comprise the minimum errors can be obtained as shown in Figure 4. Three different neural approaches are shown in this figure. It is obviously seen that test points are required to get more accurate outputs. Therefore, the input database is composed of training and test inputs. In this study, 20% of the input database was used as test inputs while the remaining part was utilized as training database. The test inputs were selected randomly from the input database.

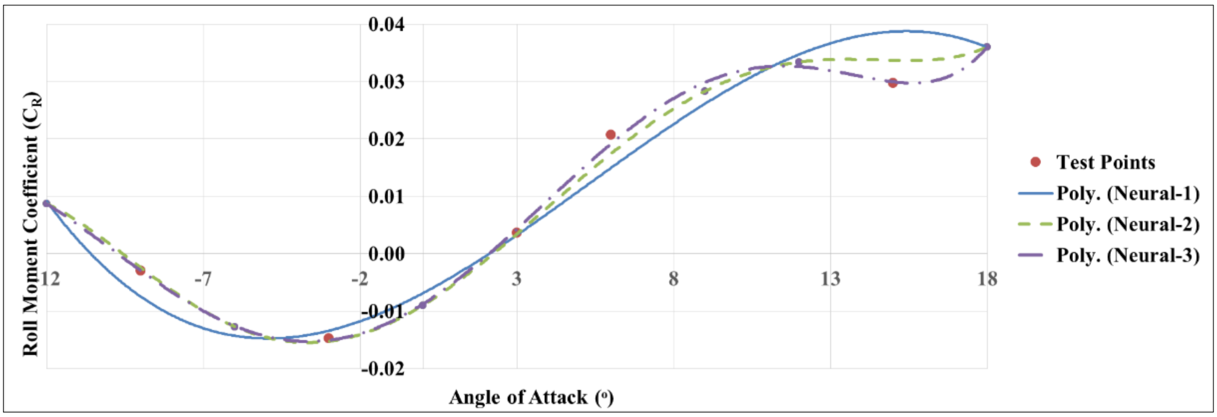


Figure 4. Training possibilities of a neural network

For the validations of NNGA, three different approach are used. Firstly, the fit performance model shown in Eq.-1 was applied [14]. In this model, t indicates target value while d_m does neural network outputs. In this study, target values are computed by CFD analyses. As the second approach, the absolute mean error between NNGA and CFD analyses are investigated. Lastly, ratio of maximum error to mean value of CFD analyses are obtained and compared.

$$\mathrm{FIT} = 100\left(1-\sqrt{\frac{\sum(t-d_m)^2}{\sum(t-mean(t))^2}}\right) \tag{1}$$

In validations; CD, CL and CY indicate the drag, lift and side force coefficients while CR, CM and CN do the roll, pitch and yawing moments. In addition, CHMAL, CHMEL and CMHR represent the hinge moment coefficients of left aileron, left elevator and rudder. As the first validation case, the datasets given in Table 4 are extracted from the aerodynamic database and computed by NNGA. Each dataset has all angle of attacks given in Table 1. Their results are compared with CFD analyses results and performance of NNGA is conducted with Eq.1 and other approaches mentioned above. In addition to NNGA, the extracted datasets are computed with the first and second order polynomial curve fitting techniques and compared with the results of NNGA.

DOI: 10.13009/EUCASS2017-226

Table 4. Datasets of the 1st Validation Case

Mach Number	Side Slip Angle	Aileron	Elevator	Rudder	Number of Data
0.2, 0.6	10	-10/+10	0	0	22
0.2, 0.6	10	+5/-5	0	0	22
0.2, 0.6	0	+15/-15	0	0	22
0.2, 0.6	0	-5/+5	0	0	22
0.2, 0.6	20	-15/+15	0	0	22
0.2, 0.6	20	0/0	0	0	22
0.4, 0.8	20	-10/+10	0	0	22
0.4, 0.8	20	+5/-5	0	0	22
0.4, 0.8	10	+15/-15	0	0	22
0.4, 0.8	10	-5/+5	0	0	22
0.4, 0.8	0	-15/+15	0	0	22
0.4, 0.8	0	0/0	0	0	22
0.2	0	0/0	-20	0	11
0.4	0	0/0	-10	0	11
0.6	0	0/0	+10	0	11
0.8	0	0/0	+20	0	11
0.2	0	0/0	0	-20	11
0.4	0	0/0	0	-10	11
0.6	0	0/0	0	+10	11
0.8	0	0/0	0	+20	11
0.6	10	0/0	0	-20	11
0.8	10	0/0	0	-10	11
0.2	10	0/0	0	+10	11
0.4	10	0/0	0	+20	11
0.8	20	0/0	0	-20	11
0.2	20	0/0	0	-10	11
0.4	20	0/0	0	+10	11
0.6	20	0/0	0	+20	11

During the first validation case four different approaches of NNGA were utilized:

1. All of the validation points in Table 4 were computed by NNGA and none of them was used as training or test input.
2. 20% of the validation inputs were used as training inputs.
3. 20% of the validation inputs were used as test inputs.
4. 10% of the validation inputs were used as training inputs while 10% of them were included as test inputs.

Results of the first validation case are shown in Figure 5, Figure 6 and Figure 7. Also, the results of 1st & 2nd order polynomial curve fittings are given in these figures for the corresponding validation datasets.

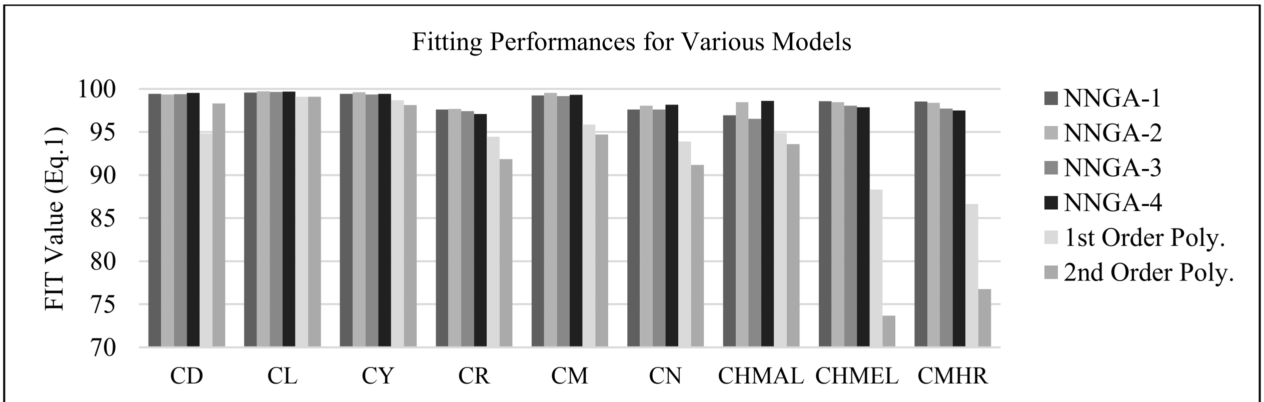


Figure 5. FIT Values of Validation Dataset for the 1st Validation Case

DOI: 10.13009/EUCASS2017-226

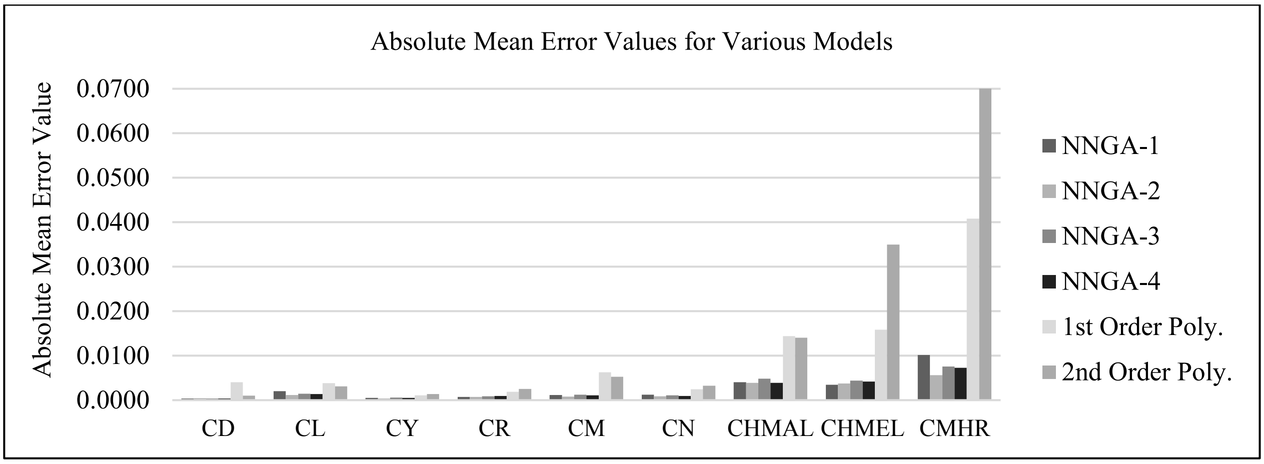


Figure 6. Absolute Mean Error Value of Validation Dataset for the 1st Validation Case

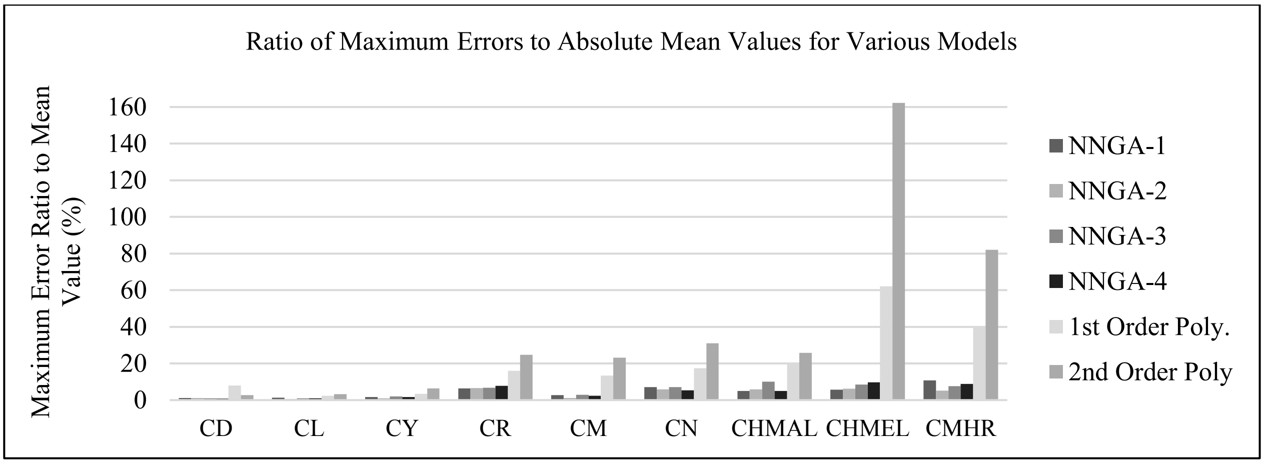


Figure 7. Ratio of Maximum Error to Absolute Mean Value of Validation Dataset for the 1st Validation Case

As seen from Figures 5 to 7, the second (NNGA-2) approach provides more accurate results than other NNGA approaches. Also, it provides superior performance as compared with polynomial curve fittings. Although the combination of the 1st and 2nd order polynomial curve fitting techniques can be helpful to compute force coefficients, a surrogate model like NNGA is required for moment coefficient calculations.

As the second validation case, the validation dataset is selected randomly from the aerodynamic database and it is computed by NNGA-2. This validation case shows the performance of NNGA to compute the lost or erroneous data and to select the smaller size of training and test inputs. The validation results with respect to the ratio of validation data are shown in Figure 8, Figure 9 and Figure 10. In this figure, 70% means that 70% of the aircraft CFD database was randomly selected as validation dataset and computed by NNGA-2.

DOI: 10.13009/EUCASS2017-226

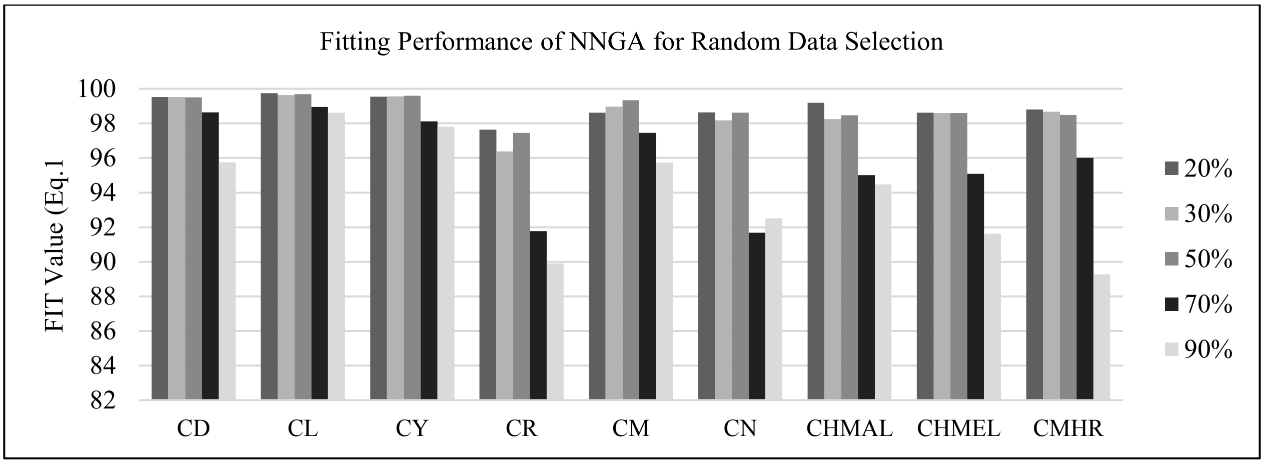


Figure 8. FIT Values of Validation Dataset for the 2nd Validation Case

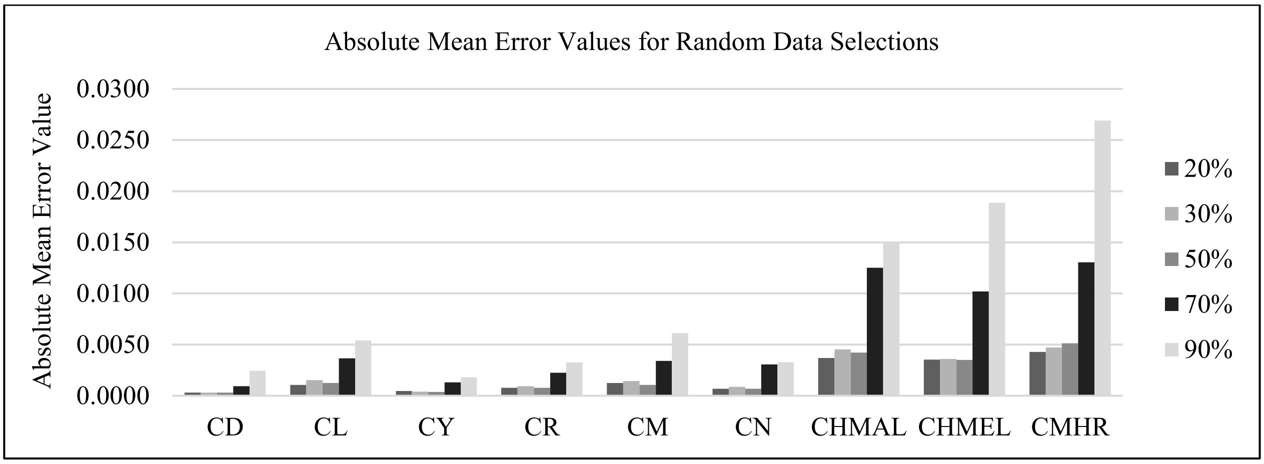


Figure 9. Absolute Mean Error Value of Validation Dataset for the 2nd Validation Case

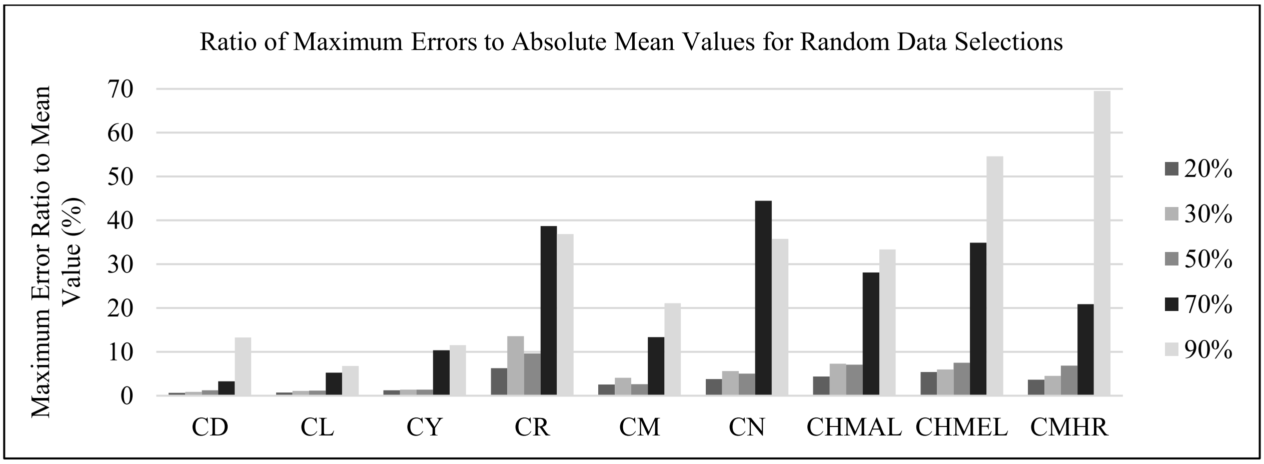


Figure 10. Ratio of Maximum Error to Absolute Mean Value of Validation Dataset for the 2nd Validation Case

As shown in Figure 8, Figure 9 and Figure 10, the force coefficients and the pitch moment coefficient of the given database can be accurately computed by utilizing only 30% of CFD database as training and test inputs. However, 50% of CFD database is required to compute roll, yaw and hinge moment coefficients precisely. It should be noted that this ratio is acceptable for the given database. It may lead higher number of errors for other types of databases such as the

DOI: 10.13009/EUCASS2017-226

ones not including various Mach numbers or control surface deflections. Therefore, training and test inputs should be carefully selected with respect to the structure of the whole database. Sample comparison plots of these coefficients are shown in Figure 11, Figure 12 and Figure 13.

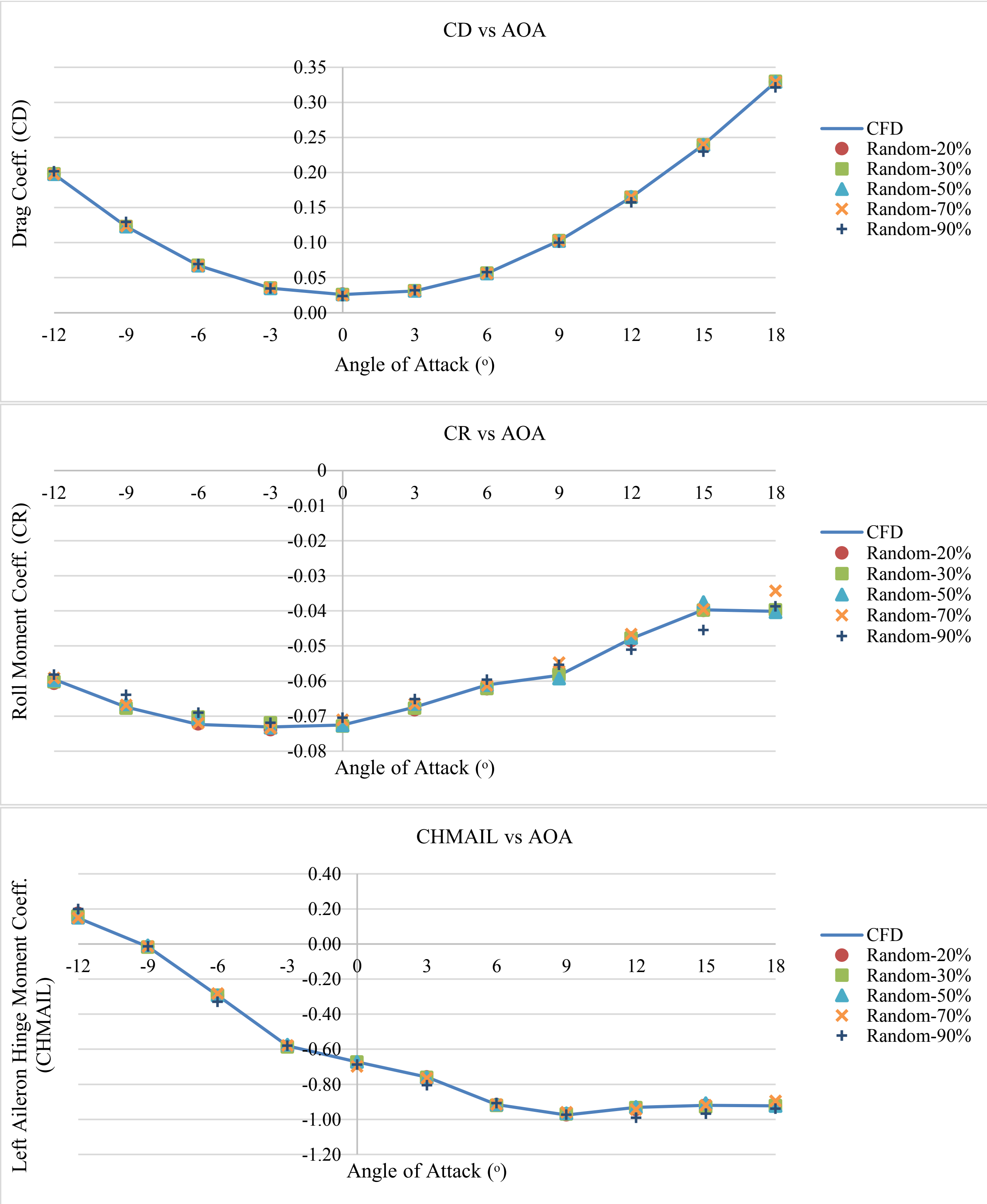


Figure 11. Response of drag force, roll moment and left aileron hinge moment coefficients for left aileron=15°, right aileron=-15°, elevator=0°, rudder=0°, Mach=0.6, Beta=0°

DOI: 10.13009/EUCASS2017-226

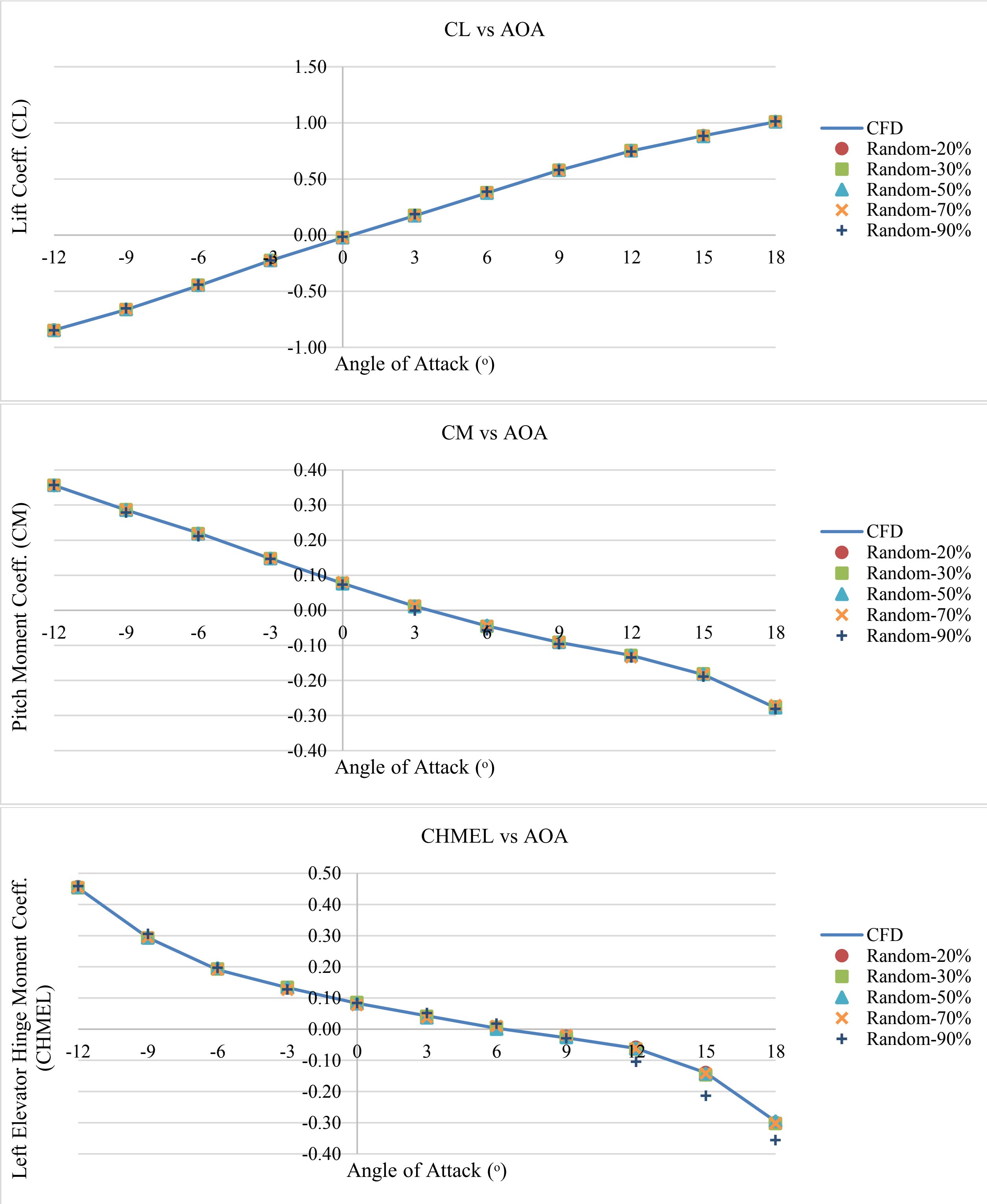


Figure 12. Response of lift force, pitch moment and left elevator hinge moment coefficients for left aileron=0°, right aileron=0°, elevator=10°, rudder=0°, Mach=0.6, Beta=0°

DOI: 10.13009/EUCASS2017-226

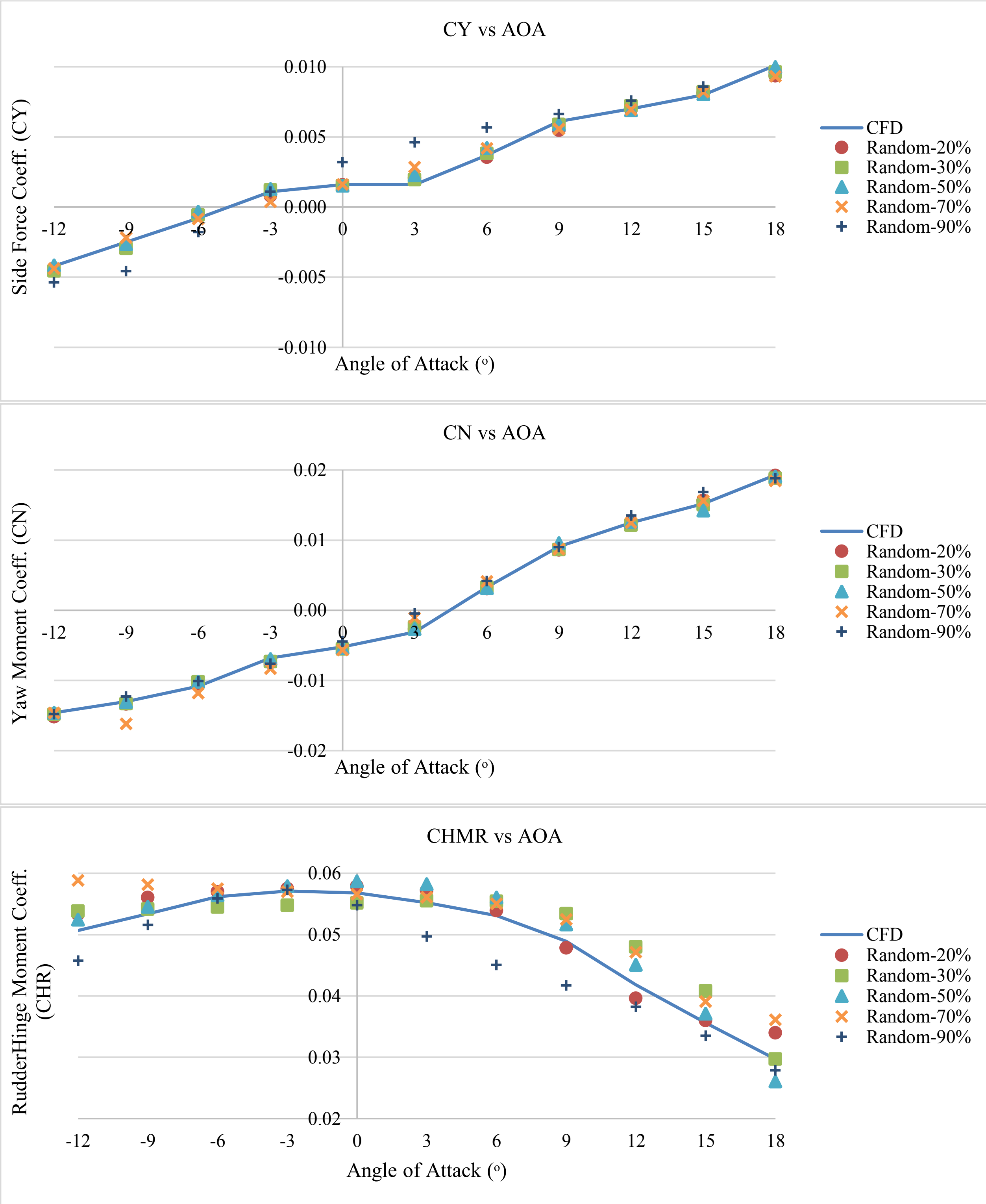


Figure 13. Response of side force, yaw moment and rudder hinge moment coefficients for left aileron=0°, right aileron=0°, elevator=0°, rudder=20°, Mach=0.2, Beta=10°

DOI: 10.13009/EUCASS2017-226

6. Conclusion

In this study, a four-layered MLP neural network model with two hidden layers is introduced and validated. The number of neurons in hidden layers and initialization parameters including initial layer weights, biases and mu coefficient are optimized by a genetic algorithm in this model. Levenberg-Marquardt backpropagation algorithm is selected as training algorithm. The model is called as NNGA. It can be helpful to improve an existent database or to shorten the computational period. To validate the model, a generic aircraft is designed and its aerodynamic database is generated by CFD analyses. The database includes force, moment and hinge moment coefficients of the aircraft with respect to control surface deflections, Mach number, angle of attack and side slip angle. The model is compared with various datasets from this database and 1^{st} & 2^{nd} order polynomial curve fits. The validations shows that much more accurate results observed for NNGA. In fact, there is no need to any CFD analyses to get 50% of CFD database since this part can be computed accurately by NNGA. Although force coefficients and pitch moment coefficient can be calculated accurately by 1^{st} & 2^{nd} order polynomial curve fits, a surrogate model is required for the prediction of yaw, roll and hinge moment coefficients. As future work, a selection algorithm that determines the training and test inputs for NNGA will be focused to minimize the period of aerodynamic database generations.

References

[1] de Paula, A. A., Porto, F. d. M., de Sousa, M. S. and Cunha Junior, S. S. da. 2016. Aerodynamic Longitudinal Coefficient Modeling During Aircraft Design Phases. In: *AIAA Modeling and Simulation Technologies Conference*, Washington, D.C.

[2] Purinton, D. C., Blevins, J. A., Pritchett, V., Haynes, D. and Carpenter, M. 2011. Aerodynamic Characterization and Simulation of a Solid Rocket Booster During Reentry Flight. In: *49th AIAA Aerospace Sciences Meeting*. Orlando,Florida.

[3] Padilla, J. F., and Boyd, I. D. 2006. Assessment of Rarefied Hypersonic Aerodynamics Modeling and Windtunnel Data. In: *9th AIAA/ASME Joint Thermophysics and Heat Transfer Conference*. San Francisco, California.

[4] Gusman, M. R. and Barad, M. F. 2011. Aerodynamic Database Generation for SRB Separation from a Heavy Lift Launch Vehicle. In: *29th AIAA Applied Aerodynamics Conference*.

[5] Nicolosi, F., Ciliberti, D., Vecchia, P. D. and Corcione, S. 2016. Aerodynamic design guidelines of an aircraft dorsal fin through numerical and experimental analyses. In: *34th AIAA Applied Aerodynamics Conference*. Washington, D.C.

[6] Mi, B. g. , Zhan, H. and Chen, B b. 2017. New Systematic CFD Methods to Calculate Static and Single Dynamic Stability Derivatives of Aircraft. *Mathematical Problems in Engineering.* vol. 2017.

[7] Smith, C.. 2015. Surrogate Models for Aerodynamic Performance Prediction Department of Computing. Phd Thesis. Faculty of Engineering and Physical Sciences, University of Surrey.

[8] Wallach, R., Mattos, B. S. and Girardi, R. d. M. 2006. Aerodynamic Coefficient Prediction of a General Transport Aircraft Using Neural Network. In: *25th International Congress of the Aeronautical Sciences*.

[9] Lee, H. M., Hur, N. K. and Kwon, O.-J. 2015. Aerodynamic Design Optimization of UAV Rotor Blades using a Genetic Algorithm. In: *ANBRE*. Incheon,Korea.

[10] García, J., Muñoz-Paniagua, J. and Crespo, A. 2011. Aerodynamic Optimization of High Speed Trains Nose Using a Genetic Algorithm and Artificial Neural Netwroks. In: *An ECCOMAS Thematic Conference CFD&Optimizaton*, Antalya,Turkey.

[11] Elshaer, A., Bitsuamlak, G., and El Damatty, A. 2016. Aerodynamic Optimization To Reduce Wind Loads On Tall Buildings. In: *Resilient Infrastructure*. London.

[12] Rojas, R. 1996. Neural Networks: A Systematic Introduction, Berlin: Springer-Verlag.

[13] Dao, S. D., Abhary, K. and Marian, R. 2016. Maximising Performance of Genetic Algorithm Solver in Matlab. In: *Engineering Letters 24*.

[14] Boely, N. and Botez, R. M. 2010. Identification and Validation of a F/A-18 Model Using Neural Networks. In: *AIAA Atmospheric Flight Mechanics Conference*. Toronto, Ontario Canada.