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Aerodynamic Database Generation with Optimized Artificial Neural Network and a Design of Experiment Technique

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Abstract
Flight tests, wind tunnel tests, empirical and theoretical methods, and CFD analyses are the ways that can be used for the aerodynamic database generation of an aircraft. To observe an aircraft's stability and control characteristics, flight performance and handling qualities or to design a control system, its aerodynamic database is essential. In this paper optimized neural network code called NNGA which is presented in EUCASS-2017 is used to decrease computational effort for the full flight aerodynamic database generation. Moreover, a design of experiment approach is performed to reduce the number of required flight conditions and control surface deflections for the database. D-optimal and V-optimal criterion were compared for design of experiment approach.

1. Introduction

Stability, control, performance characteristics and handling qualities of an aircraft in the flight envelope are main aspects. In order to obtain the flight characteristics of an aircraft, aerodynamic database is generated. Aerodynamic database consists of static coefficients, static and dynamic derivatives which are force and moment coefficients of aircraft and hinge moments of control surfaces of the aircraft. These derivatives and coefficients variate with flight conditions which are Mach number, angle of attack, sideslip angle, deflections of control surfaces and other moving equipment. Therefore, aerodynamic database is a combination of all these parameters which is generated by theoretical and empirical methods, CFD analyses, wind tunnel tests and flight tests. The empirical methods are suitable to aerodynamic database for aircraft at conceptual design phase, due to the low precision requirements, while wind tunnel testing method has advantage to obtain aerodynamic forces and moments directly. However, wind tunnel testing method is highly expensive and hard to obtain dynamic derivatives due to the complex wind tunnel geometry [1]. Computational fluid dynamics (CFD) solvers offers high fidelity results for generation of static and dynamic derivatives and coefficients [2]. Aerodynamic database of Hyper-X Launch Vehicle stack configuration was obtained by wind tunnel test method to evaluate longitudinal stability derivatives and to obtain detailed surface pressure distribution at selected locations, as well as the database was obtained by CFD method to predict aerodynamic performance at flow conditions where no experimental data is available and for component loads for mechanical design and aero-elastic analyses [3].

Any modification to the geometry and flight conditions such as deflections of the control surfaces may result with increased computational time and cost. There are some methods that can be used to reduce computational time and cost for database generation. In order to optimize analyze points and to minimize its cost, response surface models, neural networks, cubic spline fits can be employed [4].

There are lots of studies on data analysis and geometry optimization methods with neural network algorithms [5]. Data from experimental and numerical simulations can be fused together to generate an efficient archive database by neural network approach. Space shuttle vehicle longitudinal and lateral coefficient database prediction was generated by neural network architecture [6].

Design of experiment approach (DOE) may be used to reduce number of required flight conditions and control surface deflections for the database. Valid, defensible and supportable engineering conclusions and minimal expenditure of engineering runs, time and money may be benefits of DOE approach [7].

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In this paper, generic model of Northrop T-38 Talon jet aircraft was used as a platform. Its wing, horizontal tail, and vertical tail airfoils are modified. Full flight aerodynamic database for the platform is generated with an optimized neural network code which is called NNGA. The code is the optimized version of Matlab's neural network toolbox and presented in EUCASS-2017 [8]. In order to reduce the number of conditions and control surface deflections required in flight envelope, design of experiment approach was performed. Moreover, 90%, 60%, and 30% of database points were determined by these methods. A Reynolds-averaged Navier Stokes (RANS) flow solver was used as a computational tool for all database points.

2. Design of Experiment (DOE)

Design of experiment is a method of data production to actively manipulate data to improve the quality of information and to eliminate redundant data. In order to estimate model parameters accurately for sufficient information in a short period of time, DOE approach is essential to determine data points.

Design space comprises of factors, which are variables of the space, levels that are definition of factors, regression parameters and error (Measurement errors etc.). Equation 1 shows the design problem definition. $X^{(nxp)}$ is design matrix (factor), $\beta^{(px1)}$ is vector regression parameters, $y^{(nx1)}$ is vector of observations and $\epsilon^{(nx1)}$ is error vector [9].

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\epsilon} \tag{1}$$

Error is separated into two parts. One is pure error and the second is error due to response surface model. CFD errors are pure errors due to that they cannot calculated for being input dependent. Besides, this errors can be negligible or can be calculated with uncertainty quantification. Hence, ϵ can be assumed as model error for CFD cases. Thus, model is appropriate if error is lower [10].

DOE methods are statistical methods that are used to determine the effects of factors on responses and create a response surface to identify intermediate response values without replicating experiment.

Design of experiment methods were developed with strategies. An experiment starts with best-guess approach such as initial guess and guess combination of factors levels. Design of experiment methods are ways to guess these combination of factors [10].

There are classical and modern design of experiment techniques. Classical DOE was born with laboratory experiments while modern DOE was evolved after computer based experiments. There are two main differences between classical and modern DOE approaches. These are; [11]

1. Random error existing in computer experiments as a difference from laboratory experiments.
2. The choice of probability distribution functions associated with design parameters

Methodology for classical DOE is that put sample points at the extremes of parameter space, since this method is more reliable trend extraction in the presence of non-repeatability. Therefore, classical DOE techniques are suitable for designs such as central composite design, full- and fractional-factorial designs. Besides, this technique assumes that possible design parameters are uniformly distributed between upper and lower bound. Modern DOE techniques were developed after deterministic computer simulations which have repeatability. In order to extract trend information accurately, space filling methods such as quasi-Monte Carlo sampling, orthogonal array sampling, and Latin hypercube sampling are employed to the methodology. Moreover, modern DOE handle design parameters both uniform and non-uniform probability distributions such as Gaussian or Weibull [11].

Improved computer simulations caused new problems such as non-uniform level of factor requirements or cost which is increased with simulation points. In order to satisfy these problems, modern DOE methods were modified with optimal design methods.

A design problem need a suitable criterion. D-optimality criterion put emphasis on the quality of the parameter estimation. Therefore, this criterion is a way to minimize the volume of design space by maximizing determinant of the space. V-Optimality criterion (also known as IV-Optimality or Q-optimality) is to minimize the integrate prediction variance over the region of interest [9].

In this paper, Model-Based Calibration Toolbox of Matlab was used to determine design space. Moreover, optimal methods were selected due to the fact that error of the problem is model error and factor levels are non-uniform. D-optimal, and V-optimal methods are used to generate design space.

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3. Neural Network

In this study a feed forward neural network (MLP) with Levenberg-Marquardt back propagation training algorithm is used. The algorithm consist of layers which have artificial neurons interconnected to other neurons. Layer architecture is selected as four-layered network with two hidden layers. Figure 1 shows the network with hidden layers having 2 neurons. The details of the algorithm is presented in EUCASS 2017 [8] .

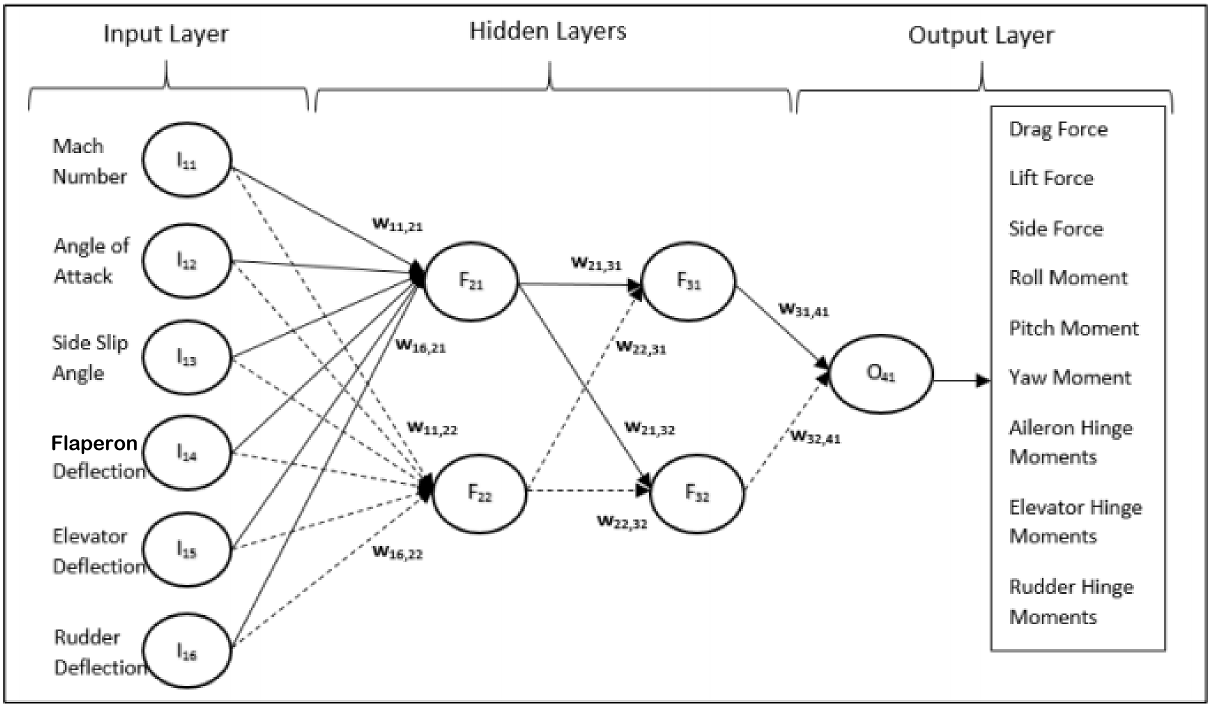

Figure 1: Four-Layered Network

4. Geometry and Database Description

To perform neural network model (NNGA) an aerodynamic database was generated. Generic of Northrop T-38 Talon jet aircraft was selected as layout. Generic model of T38 was obtained from the GrabCAD [12] and selected airfoil shapes which is shown in Table 1, implemented to the aircraft. Generic rudder, horizontal tail and Flaperon positions and sizes and hinge locations were determined with engineering judgement. Figure 2 shows the generic T38 aircraft.

Table 1: Airfoil Shapes

	WING	**HORIZONTAL TAIL**	**VERTICAL TAIL**
Airfoil Shapes	NACA63206	NACA0006	NACA0007

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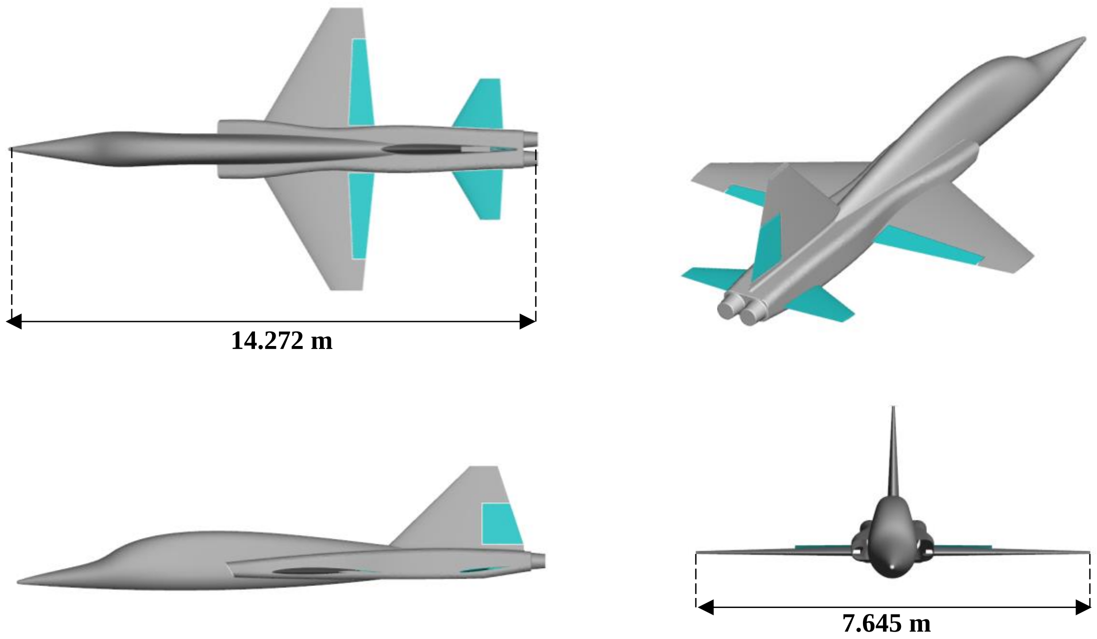

Figure 2: Top, Side, Front And Perspective View Of The Generic T38 Aircraft

RANS flow solver was used to obtain static coefficients and control surface hinge moments of the aircraft. The reference area of the aircraft is $16.734\ m^2$. The reference chord length at MAC 25% is 2.4545 m and its span is 7.646 m. K-w SST turbulence model is used in the CFD analysis.

Flight conditions and control surface deflection are determined as below tables. Mach, Angle of attack, and sideslip ranges to generate database are shown in Table 2, while deflection ranges of control surfaces are shown in Table 3. Besides, aircraft configurations are given in Table 4 and matrix sets for database according to configurations are shown in Table 5.

Table 2: Mach, Angle of Attack and Sideslip Ranges for Generated Database

SET	RANGES
Mach 1	0.2, 0.5
Mach 2	0.8, 0.95, 1.05
Mach 3	1.3
AOA1	-3, 0, 2, 5, 7, 10, 15, 20, 25
AOA2	-3, 0, 2, 5, 7, 10, 15
AOA3	0, 2, 5
BETA1	-20, -10, -5, 0, 5, 10, 20
BETA2	-10, -5, 0, 5, 10
BETA3	-5, 0, 5

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Table 3: Deflections of Control Surfaces

DEFLECTION RANGES	
RUDDER 0	0
RUDDER 1	2, 5, 10, 20, 30
RUDDER 2	2, 5, 10
RUDDER 3	2
HORIZONTAL TAIL 0	0
HORIZONTAL TAIL 1	-20, -15, -10, -5, 5, 10, 15, 20
HORIZONTAL TAIL 2	-10, -5, 5, 10
HORIZONTAL TAIL 3	-5, 5
FLAPERON 0	0
FLAPERON 1	-20, -15, -10, -5, 5, 10, 15, 20
FLAPERON 2	-10, -5, 5, 10
FLAPERON 3	-5, 5

Table 4: Aircraft Configurations for Database

CONFIGURATION	RUDDER	HORIZONTAL TAIL	FLAPERON
CLEAN	RUDDER 0	HORIZONTAL TAIL 0	FLAPERON 0
RUDDER DEFLECTED	RUDDER 1 RUDDER 2 RUDDER 3	HORIZONTAL TAIL 0	FLAPERON 0
HORIZONTAL TAIL DEFLECTED	RUDDER 0	HORIZONTAL TAIL 1 HORIZONTAL TAIL 2 HORIZONTAL TAIL 3	FLAPERON 0
FLAPERON DEFLECTED	RUDDER 0	HORIZONTAL TAIL 0	FLAPERON 1 FLAPERON 2 FLAPERON 3

Table 5: Matrices of Aircraft Configurations

CLEAN CONFIGURATION MATRIX					
	CONFIGURATION	**MACH**	**AOA**	**BETA**	**# OF ANALYSES**
SET1	CLEAN	MACH 1	AOA1	BETA1	126
SET2	CLEAN	MACH 2	AOA2	BETA2	105
SET3	CLEAN	MACH 3	AOA3	BETA3	9
RUDDER DEFLECTED CONFIGURATION MATRIX					
	CONFIGURATION	**MACH**	**AOA**	**BETA**	**# OF ANALYSES**
SET1	RUDDER 1	MACH 1	AOA1	BETA1	630
SET2	RUDDER 2	MACH 2	AOA2	BETA2	315
SET3	RUDDER 3	MACH 3	AOA3	BETA3	9
HORIZONTAL TAIL DEFLECTED CONFIGURATION MATRIX					
	CONFIGURATION	**MACH**	**AOA**	**BETA**	**# OF ANALYSES**
SET1	HORIZONTAL TAIL 1	MACH 1	AOA1	BETA1	1008
SET2	HORIZONTAL TAIL 2	MACH 2	AOA2	BETA2	420
SET3	HORIZONTAL TAIL 3	MACH 3	AOA3	BETA3	18
FLAPERON DEFLECTED CONFIGURATION MATRIX					
	CONFIGURATION	**MACH**	**AOA**	**BETA**	**# OF ANALYSES**
SET1	FLAPERON 1	MACH 1	AOA1	BETA1	1008
SET2	FLAPERON 2	MACH 2	AOA2	BETA2	420
SET3	FLAPERON 3	MACH 3	AOA3	BETA3	18

Clean configuration was solved with and without boundary layer meshes separately for full aircraft, while deflected cases were analyzed without boundary layer mesh for half body by assuming that aircraft is symmetric and identical flight conditions. Boundary layer delta is added to control surface deflected cases and database generated

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with total 4086 number of runs. The analyses which were solved with half body (excluding sideslip cases) and without boundary layer mesh decreased computation time.

90%, 60% and 30% points of the database were selected via DOE methods, D-optimal, and V-optimal methods separately, and was used as training, test and validation inputs for NNGA.

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

Above parameters are input parameters for neural network analyses.

5. Results

In order to validate NNGA, database which is described in Table 5 was used. Flaperon, rudder, and horizontal tail deflections were investigated separately. The network weights and biases are required to minimize the error between network output and training dataset. Therefore, input database is essential for updating weights and biases. Thus, D-optimal and V-optimal DOE methods were used to select input database for network. 30%, 60% and 90% of the database were selected as input for the two DOE methods and whole database is generated with NNGA, then they compared with CFD results.

Fit performance model which is shown in Equation 2 was applied for validation of NNGA [13]. In the equation, t indicates target value and d_m indicates neural network outputs. In this paper target values were computed by CFD analyses.

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

CD, CL, and CY indicates drag, lift and side force coefficients respectively, while CR, CM, and CN indicates roll, pitch, and yawing moments.

In validation cases firstly D-optimal and V-optimal DOE methods which determines input database were compared for rudder, horizontal tail, and flaperon deflected cases. Figure 3 shows the fit comparison of the D-optimal and V-optimal methods for input database selection. Generated input databases have same data number but the data selection methods are different. Figure 3 shows the database which is generated with minimum input values due to determine the most effective DOE method.

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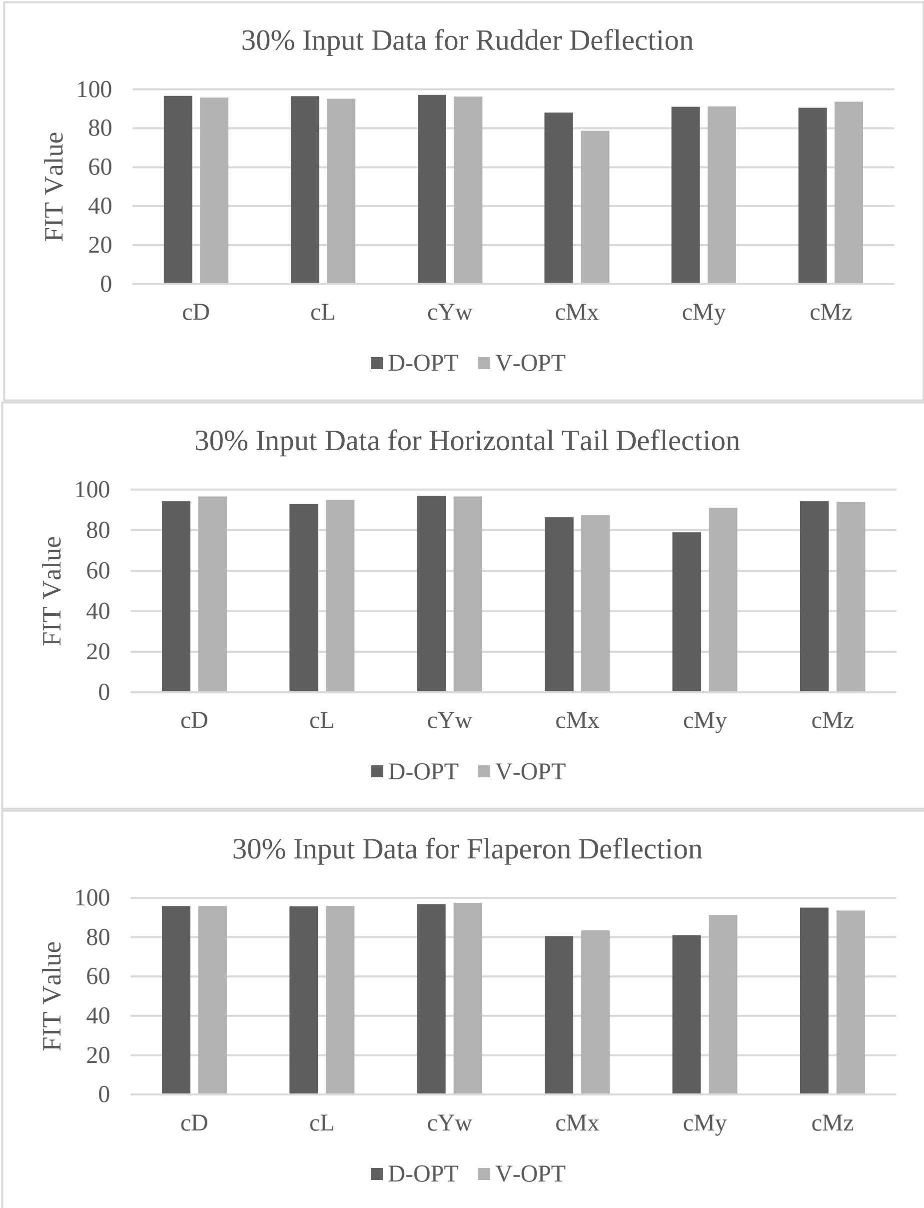

Figure 3: Fit Comparison of D-Optimal and V-Optimal Methods for Different Input Database Selections

CY, CL, CD, and CN have a continuous and predictable trend for control surface deflected cases or different flight conditions. Due to the fact that the estimation for these parameters with NNGA is more accurate. While, CM, and CR curves have discontinuous trend according to the deflections and flight conditions. Therefore, the prediction of these moment coefficients are not easy as well as other parameters. Yawing moment and rolling moment is directly affected by rudder deflection. While pitching moment and rolling moment parameters are affected by horizontal tail and flaperon deflections. Results show that, V-Optimal DOE method which is used to select input database is more accurate than the D-optimal method even if number of input data is lower. Moreover, CR and CM estimation is a tough problem.

Secondly, number of input database is an important parameter to decrease error. Figure 4 shows the fit comparison for CFD and NNGA results for database which was generated with different number of input data.

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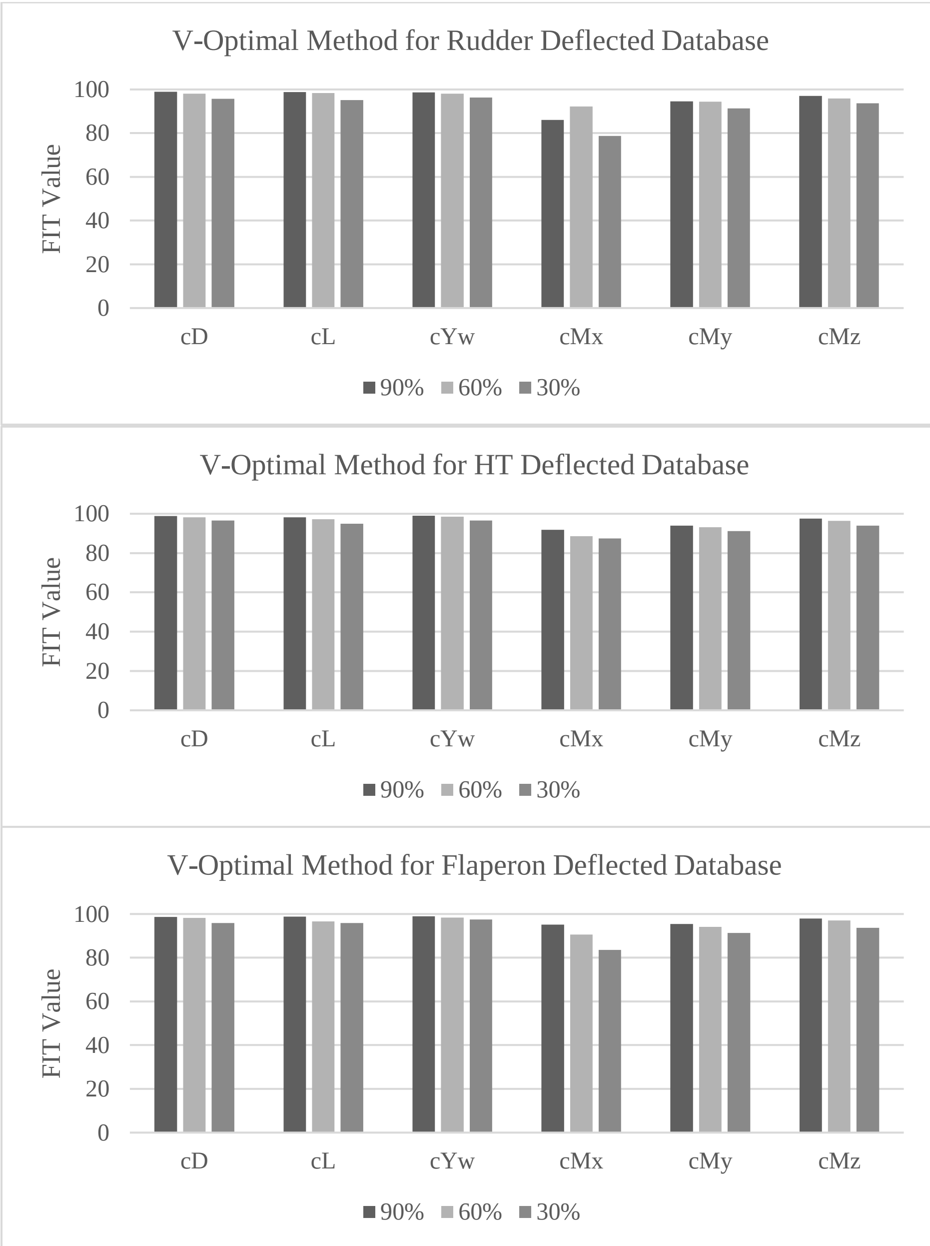

Figure 4: Effect of Number of Input Data

Results shows that if the number of input database is increased, error between CFD and NNGA results minimize. In order to obtain accurate results, that, the algorithm must be feed with higher number of data, can be said generally. However, for rudder deflected case the maximum input data gave a lower fitting value than the medium input data while estimating rolling moment coefficient. It can be explained by that, rolling moment coefficient have a discontinuity trend and NNGA is a non-parametric response surface model. Neural network code select 10% of training data as test data. If test data would be given to the algorithm as outsource without letting the algorithm to select from training data, accuracy is going to increase. Rolling moment of the first chart of the figure 4 is a result of randomly selected test data from the training data. Due to the error which is occurred because of the validation with test data, results with this problem. Results also show that even if the input data is 30% of the full database fit values are higher than 80. Nevertheless, comparison plots should be investigated to determine the response of the FIT values.

Sample comparison plots of these coefficients are shown in Figure 5, Figure 6, and Figure 7 respectively.

The main points of directional stability, first when the sideslip angle is zero, aircraft should tend to remain in equilibrium. Second, aircraft should produce opposite moment across the moments produced from sideslip angle.

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Initial tendency of an aircraft returning from a sideslip angle is called as static directional stability. Main derivative is CN vs sideslip angle for the static directional stability, and it should be positive for a directionally stable aircraft. Rudder is the main control surface which controls the directional behavior of the aircraft. Therefore, CN vs sideslip angle is indicated for rudder database. Figure 5 shows the important parameters for rudder deflected case and results show that even with low number of input data is enough to predict rudder deflected case.

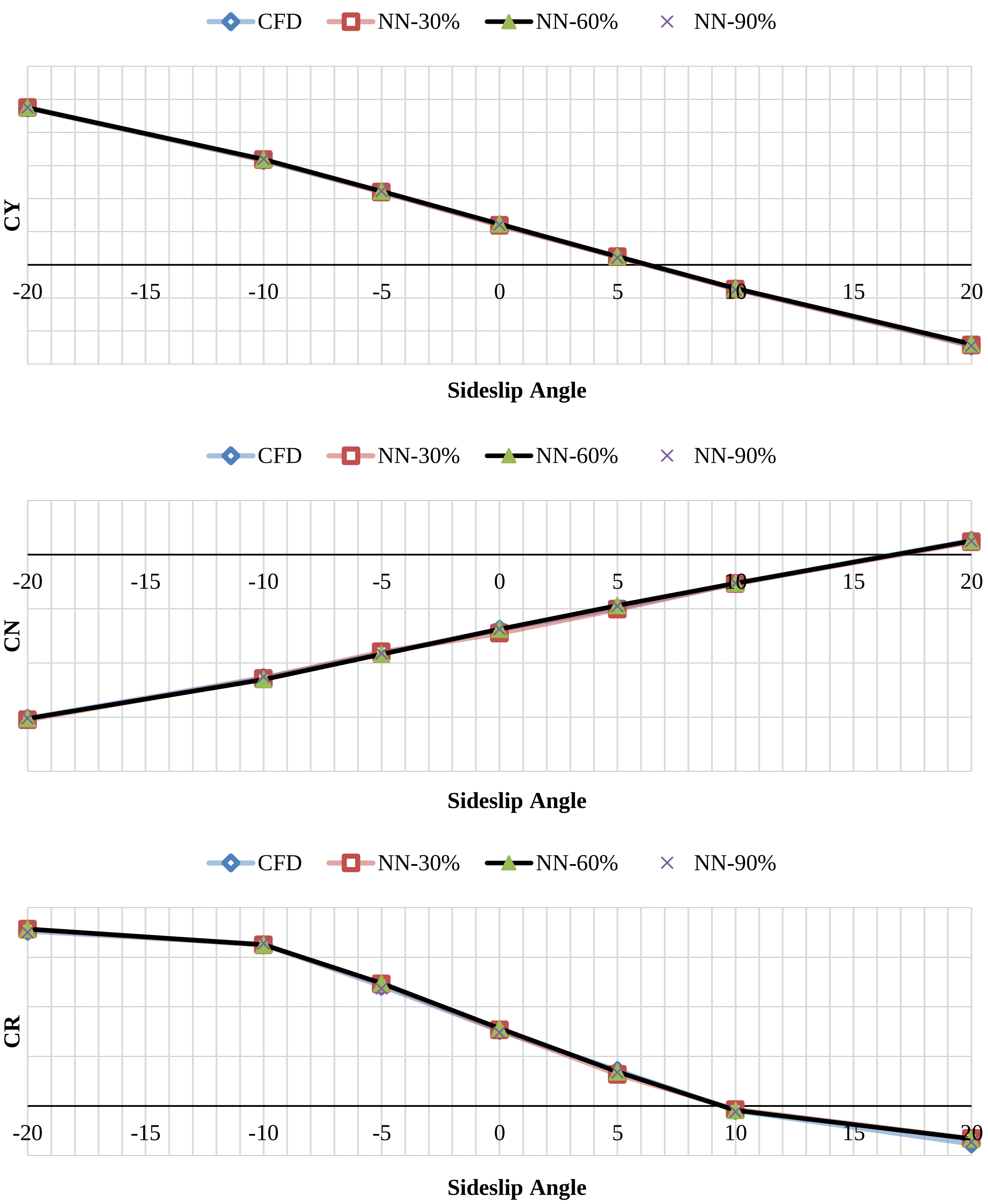

Figure 5: Response of Side Force, Yawing and Rolling Moment Coefficients for Left Flaperon=0, Right Flaperon=0, Horizontal Tail=0, Rudder=30, Mach= 0.5, Alpha=0

The momentary changes in angle of attack and lift coefficients generates resultant aircraft pitching moment which is related with longitudinal static stability. Therefore, CM vs alpha is the primary stability derivative for longitudinal static stability. Because of that, CM vs alpha derivative is indicated for horizontal tail database. Figure 6 shows the affected parameters with horizontal tail deflection. Results show that CD curve can be obtained even

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with lower input data. While in order to estimate CL and CM curves lower number of input data is not enough, at least medium input data is needed to obtain these curves.

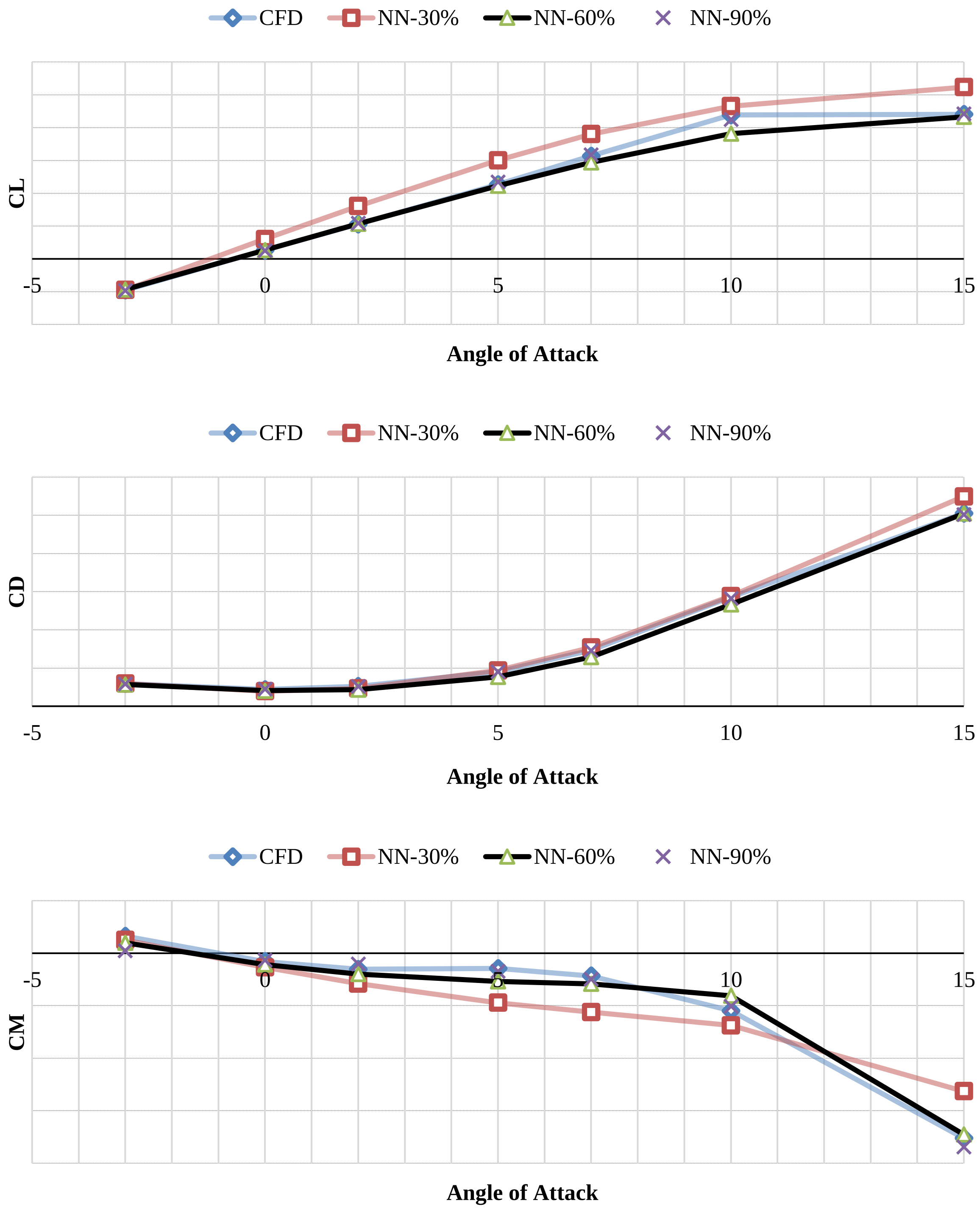

Figure 6: Response Of Lift and Drag Force Coefficients, and Pitching Moment for Left Flaperon=0, Right Flaperon=0, Horizontal Tail=10, Rudder=0, Beta=0, Mach=0.8

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Rolling moment coefficient vs sideslip angle is the main derivative for the static lateral stability. Over the rolling moments about the x axis, aircraft tends to remain back to wings level. In this study, flaperons have the major control on lateral stability. Because of that, rolling moment vs sideslip angle is indicated for the static lateral stability. To estimate CL, CR and CN curves for flaperon deflected cases, lower number of input data is enough to generate database.

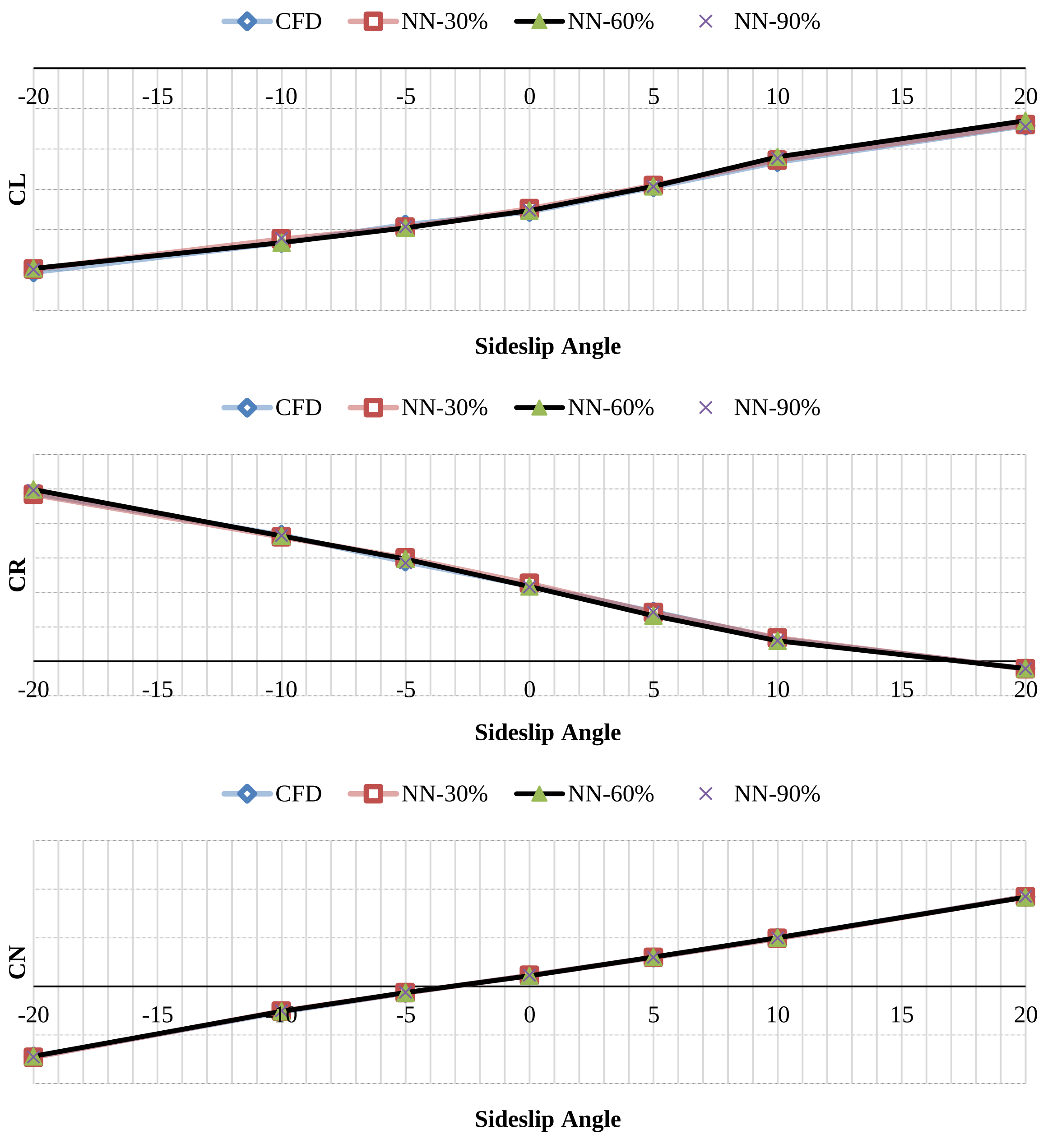

Figure 7: Response of Rolling and Yawing Moment for Left Flaperon=0, Right Flaperon=-20, Horizontal Tail=0, Rudder=0, Alpha=0

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6. Conclusion

In this study, neural networks are created for the aerodynamic database generations and design of experiment methods are employed to determine training data for NNGA. The main importance of this study is that decreasing computation time for a design by achieving accurate data with less computation. To validate the model, a platform aircraft is selected and its aerodynamic database is generated by CFD analyses. Database includes, lift, drag, and side force coefficients and rolling, pitching and yawing moment coefficients with respect to control surface deflection, Mach number, angle of attack and sideslip angle. D-optimal and V-optimal criterions of DOE are used to determine training data for NNGA. Results show that V-optimal criterion is generally more accurate than the D-optimal criterion even with lower input with the method. The accuracy is higher for lift, drag force and yawing moment coefficients even with the lower number of training data due to being continuous and predictable curve. However, rolling moment and pitching moment coefficients have discontinuous and easily varied curves with different flight conditions and control surface deflections. Therefore, these parameters are hard to predict and need higher number of input data. To obtain more accurate neural network outputs for rolling and pitching moment, at least medium level of input data is required for NNGA trainings. Moreover, neural network code select 10% of the training data as test data to validate itself. If test data would be given separated from the training data, accuracy is going to increase. The NNGA is useful algorithm to predict database with lower computational effort. Moreover it can be used to determine aerodynamic databases for conceptual design to understand the effects of the control surface deflections and flight conditions.

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