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DESIGN OF EXPERIMENT FOR WIND TUNNEL TEST AND MODELING THE DATA USİNG ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The wind tunnel experiments are one of the most common methodologies for verification of an air vehicle and generation of aerodynamic database to be used for simulation purposes. This paper summarizes a case study and approach for design of experiment that implemented for wind tunnel testing of an agile vehicle. In addition, modelling approach for the collected data and procedure of model selection is presented. Widely known Artificial Neural Networks (ANN) technique is used as modelling tool. The performances of the selected models are presented with simulations that are conducted in flight envelope using 6DoF simulation environment.

NOMENCLATURE

6DoF	=	six-degree-of-freedom
α, AoA	=	angle of attack
(A)NN	=	(artificial) neural networks
β, AoS	=	angle of sideslip
CFD	=	computational fluid dynamics
CX	=	X axis force coefficient
CY	=	Y axis force coefficient
CZ	=	Z axis force coefficient
Cl, CLL	=	X axis moment coefficient
Cm, CM	=	Y axis moment coefficient
Cn, CLN	=	Z axis moment coefficient
δ_a	=	aileron deflection
δ_i	=	i'th control surface deflection angle
δ_e	=	elevator deflection
δ_r	=	rudder deflection
DoE	=	Design of Experiment
HLS	=	Hidden Layer Size
Hz	=	Hertz
MSE	=	Mean Squared Error
OFAT	=	one-factor-at-a-time
WT	=	Wind Tunnel
Ω	=	stability axis rotation rate
ω	=	angular rates
ν	=	measurement error

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INTRODUCTION

The prediction of aerodynamic coefficients before flight test is a big challenge of newly designed air vehicles and wind tunnel testing is extensively used for this purpose. As the flight regime broadens, the conduction of wind tunnel tests also becomes challenging. This paper gives a summary of approach of wind tunnel test design and modelling for an agile air vehicle which travels through subsonic, transonic and supersonic Mach number regimes.

The control of the vehicle is achieved via four independent tail fins, and the vehicle is capable of reaching high α and β values through its flight. As a result, the flight envelope is very large which makes the multi-dimensional space that the design of experiment to be conducted vast and highly non-linear in nature. In this case study, the design of experiment for wind tunnel test is performed using a combination of one-factor-at-a-time (OFAT) and sequential or incremental space filling techniques**.** The paper continues with the modelling of the data collected for six aerodynamic coefficients of the vehicle. The Artificial Neural Networks (ANN) techniques is used in order to achieve high accuracy. The selection procedure is also presented for each coefficient. Simulation performance of the selected models is investigated.

AERODYNAMIC DEFINITIONS and 6DoF MODEL

Aerodynamic models are made of non-dimensional static and dynamic force and moment coefficients. The coefficients changes with variables which are non-dimensional parameters derived from dimensional quantities. The aerodynamic coefficient is defined as presented below;

$$C_i = C_i\left(\alpha, \beta, \delta, \frac{\Omega l}{V}, \frac{\dot{\Omega} l^2}{V^2}, \frac{\dot{V} l}{V^2}, Str, Re, Fr, M, \ldots\right)$$

where $i = X, Y, Z, l, m, n.$ (1)

Since air vehicle’s mass and inertia are significantly larger than the surrounding air mass and inertia, fluid properties change slowly. Thereby, Froude Number effect is small. Moreover, because of the quasi-steady flow assumption, the flow adjusts instantaneously to changes. This result is an exception to Strouhal number effect [Klein, Morelli, 2006]. The change in Reynolds number can also be neglected because it differs only slightly in flight. Then, the Eq. 1 becomes;

$$C_i = C_i\left(\alpha, \beta, \delta, \frac{\Omega l}{V}, \frac{\dot{\Omega} l^2}{V^2}, \frac{\dot{V} l}{V^2}, M\right) \tag{2}$$

For wind tunnel testing, the number of parameters is decreased to α, β, M, δ since it is not feasible for the dynamic components to be tested at high rate values which is a must for an agile vehicle. The Eq. 2 becomes;

$$C_i = C_i(\alpha, \beta, \delta, M) \tag{3}$$

The axis system that is used to define the aerodynamic coefficients and equations of motion is presented in Figure 1. The center of gravity of air vehicle, 'O', is the origin of both the stability and body axes. Body axis is defined as,

- Positive O_{xb} axis forward and aligned with the nose of the vehicle
- Positive O_{yb} axis points out the right wing
- Positive O_{zb} axis is directed through the downside forming a right hand rule with x_b and y_b.,

Air vehicles are simulated in 6DoF model in which the body assumed to be rigid. This assumption leads to eliminate the need to consider the interaction between individual elements of air vehicle.

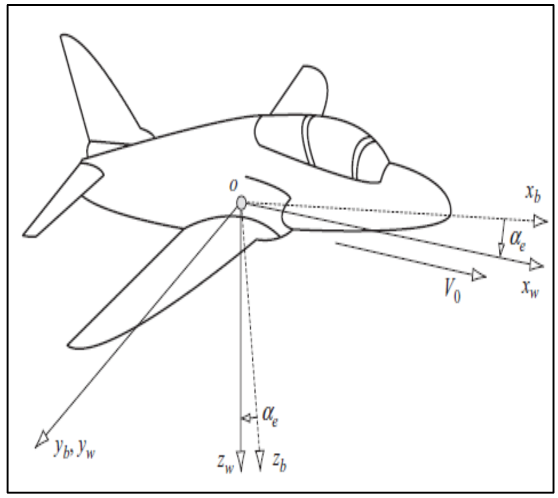

Figure 1. Air vehicle body and stability axis [Cook, 2007]

DESIGN of EXPERIMENT

Preparation of the test matrix is a vital part of wind tunnel testing. Design of Experiments (DoE) are commonly utilized for this preparation. Different approaches can be used while designing an experiment. However, they can be simplified into one-factor-at-a-time (OFAT) methods and the methods that consider multiple factors simultaneously. One needs to consider the space to be covered and the requirements of testing while selecting the right DoE method.

Wind tunnel testing of air vehicles, typically consist of angle of attack (α), angle of sideslip (β), Mach number, and control surface deflection (δi) parameters. As a result, space for the DoE is defined by these parameters. As the parameter limits grows wider, so does the test matrix. In addition, the effect of interactions of parameters is also under consideration. Both factors increase the number of test points needed to cover the space, which is an issue since the number of test points are usually limited in a test campaign.

The vehicle under consideration has parameters with wide range due to its design and function. Following the requirements for the test matrix generation given above, the DoE methods that consider multiple factors simultaneously becomes more beneficial. These methods favor the statistical modelling of the data as well. In addition, these methods can be used in an additive manner. Test matrix can be generated at multiple phases where test points on each phase is built over the previous ones. On the other hand, since the wind tunnel is also a design tool, some OFAT test points are also required in the test matrix to understand the aerodynamic characteristics of the vehicle which may require test points at determined parameter values.

As a result, an approach to DoE is purposed as follows. Firstly, a uniform test matrix with OFAT approach is designed with a limited number of test points (Phase 1). Remaining test points are used to cover the space intended while simultaneously considering multiple parameters. For this study, two phases (Phase 2 & 3) are planned for the latter part with usage of space filling design methodology, [Crombecq, Dhaene, 2010; GENT University 2012].

Figure 1 represents a sample DoE result. The blue points are Phase 1 test points that are placed with OFAT method in a uniform manner. These points are used as initial points for Phase 2 test points which are generated using space filling methodology. Phase 2 points are illustrated by the red points. Finally, phase 1 and 2 points are used as initial points for Phase 3 test points.

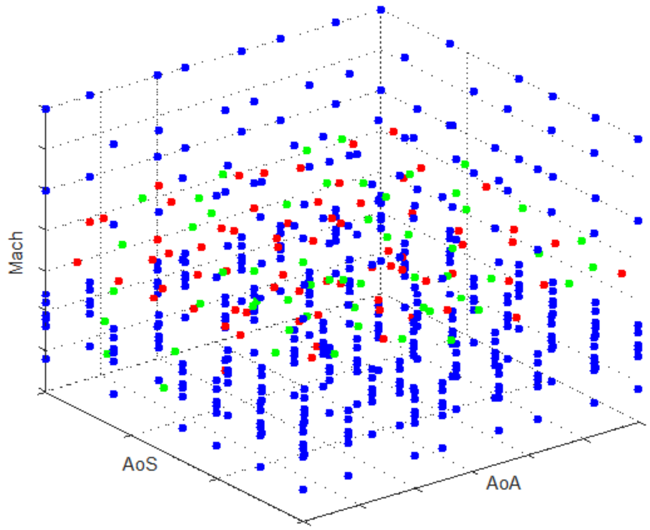

Figure 2. Sequential space-filling example in 3D domain

The resulted test matrix is presented with parallel coordinates visualization technique in Figure 3. It can be seen that the design space is fully covered, which means that the DoE approach was able to achieve the test matrix that is aimed at the beginning.

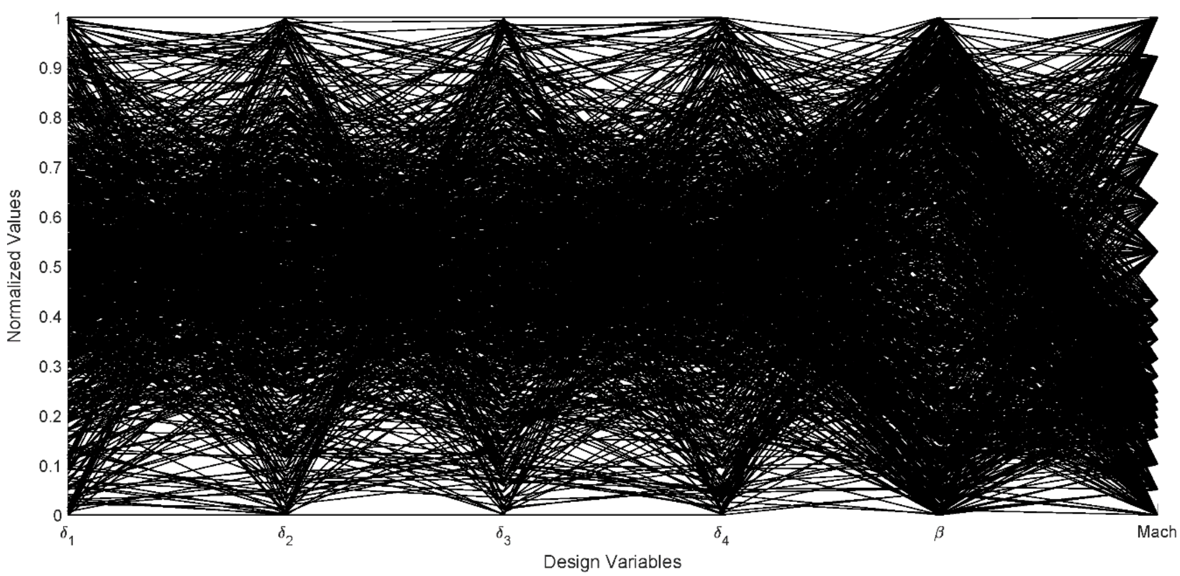

Figure 3. Parallel coordinates chart of DoE

In addition to the parallel coordinates chart given above, another technique is also applied to assess the performance of DoE. In this technique, flight simulation results of the scenario pool of the missile is run and plotted on the same axis with respect to Mach number. For example, angle of attack profile of every simulation is obtained and all of them are plotted with respect to the corresponding Mach number. That graphs are given for angle of attack and angle of sideslip with changing Mach numbers. Together with that, a final graph is plotted where angles of attack are plotted against angles of sideslip. That way, one can see the scenario coverage performance of the DoE.

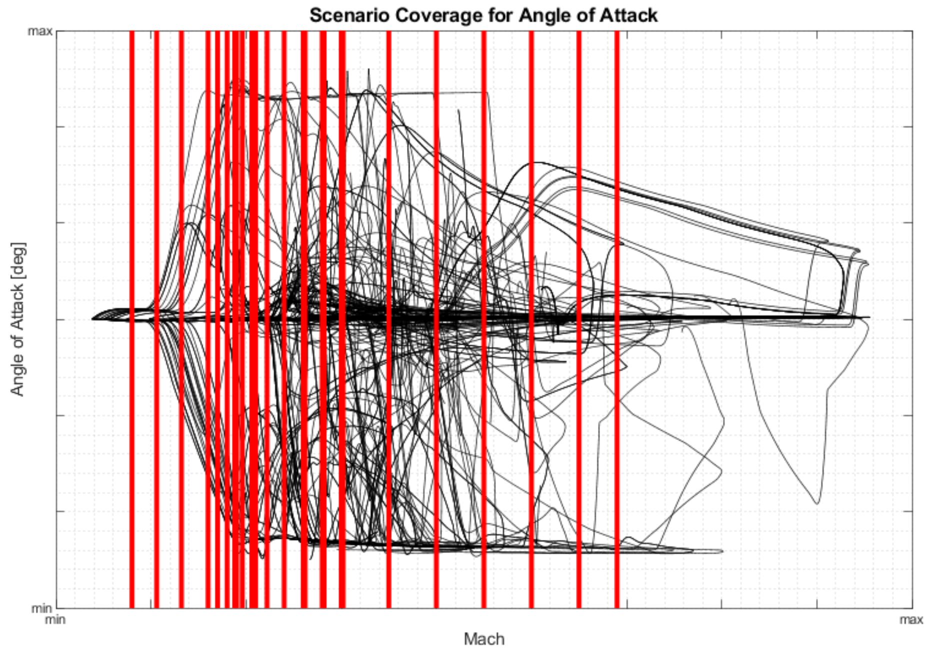

Figure 4. Scenario coverage for angle of attack

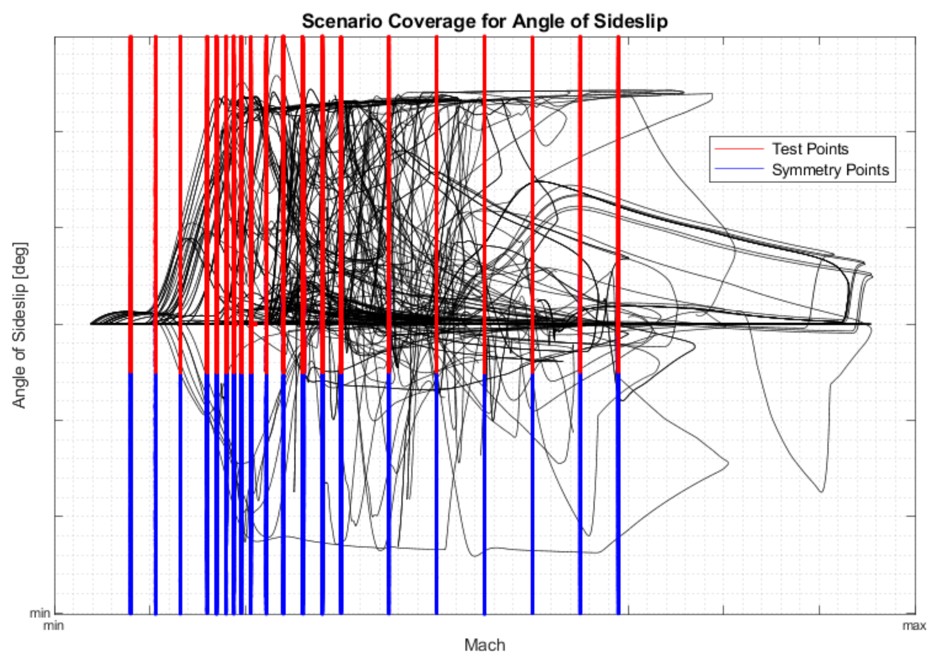

Figure 5. Scenario coverage for angle of sideslip

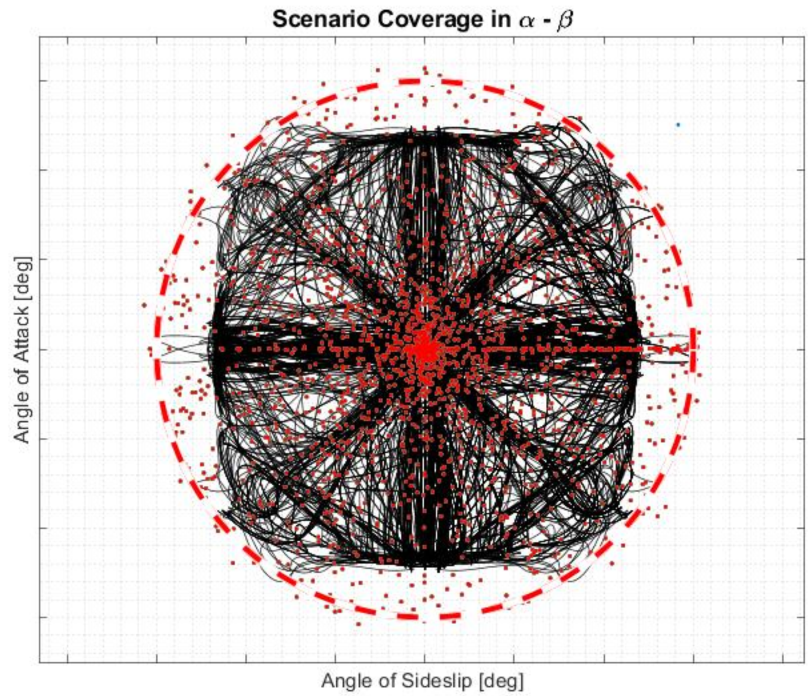

Figure 6. Scenario coverage for α-β

As can be seen from Figures Figure 4-Figure 6, test points which are represented by red points are adequately covering the flight scenario results of flow parameters in the simulation model.

MODELING

The data collected from wind tunnel tests are used for the modelling of the aerodynamic coefficients. The accuracy of the modeling is crucial since it is the sole thing that affects the simulation accuracy. Models with higher complexity and accuracy leads to higher simulation accuracy, however, as a model becomes more complex couple of issues may surface. Firstly, the model which will be used during simulations has to be able to perform in a reasonable speed. Secondly, the overfitting problem which dangers the integrity of the model in the modelling space may occur. Hence there emerges a trade-off among accuracy, performance and model integrity.

The ANN technique is selected to model the aerodynamic coefficients due to non-linear behavior of coefficients with the change of modelling parameters. The technique is one of the most commonly used non-parametric modelling techniques and used in aerospace with success [Lo, Zhao, DeLoach, 2000; Selvi, Rama, Mahendran, 2007]. The technique is quite powerful to model any kind of data, however, one needs to be careful since non-parametric methods are prone to overfitting.

A. Artificial Neural Networks

Artificial Neural Networks (ANN) is a computing technique inspired by human brain and nervous system as a network of units called neurons. The mathematical model view of a neuron as a basic building block of ANN can be shown as in Figure 7. ANN works with layers such as input layer, output layer and optional hidden layers. Input layer presents the patterns of the data and through hidden layers, where the data processing is performed, input layer makes a connection to the output layer.

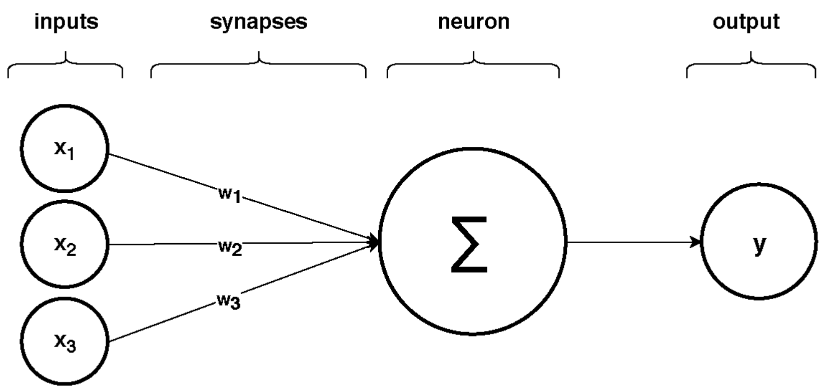

Figure 7. A simple artifical neural network, [Patel ,2003]

There are a number of different architectures of ANN to propose solution to different type of problems. Since in this study is about curve fitting to wind tunnel test data, curve fitting aspect of ANN is considered. The idea behind curve fitting is to select the suitable parameters that minimize the error over the set of data. ANN is a widely used nonlinear modeling technique that relates the output(s) with the input(s) on curve fitting problems. The most successful applications in curve fitting / modeling of neural networks are multilayer networks. This type of networks simply accepts the input values and successive layers of nodes. The outputs of neurons in a layer are inputs to neurons in the next layer. The last layer is called the output layer. Layers between the input and output layers are called as hidden layers (Figure 8).

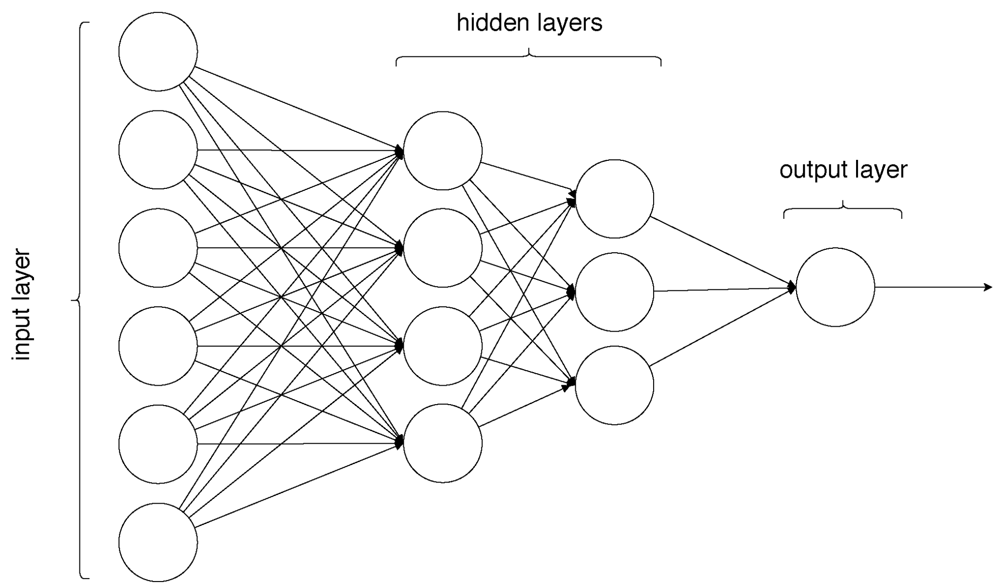

Figure 8. Multi-layer artificial neural network, [Patel ,2003]

ANN works well on large set of data with nonlinear relationships. That’s why it is appropriate to use ANN when modeling large and nonlinear aerodynamic datasets.

B. Modeling Results

Model Selection: Modeling process is not a one-step procedure. When modeling with ANN, hidden layer size is changed and models are generated. After that, model selection is performed mainly considering statistical performance. Models are generated with changing hidden layer size until the test sample error stops decreasing or a model with sufficient prediction capability is achieved.

In this paper, a model selection procedure is purposed and applied as follows. The modelling data is divided into test and training parts where 30% percent is dedicated for testing. The training data is used for attaining a model. The test data is used to evaluate the model's prediction capability which is initially evaluated by r^2 value. The next check is applied on inspecting the data by eye to see if the physical phoneme is captured or not.

As the complexity of the models are increased, the performance of the model over the test data is observed. The models that are considered to be worthy of the data at hand shall not show a significant decrease on prediction performance over the test data comparing to lower complexity models. In addition, the stability parameter over the r^2 is considered as the complexity increased. The ratio of r^2 performance over the test data and the training data is also followed to ensure that the training performance and the prediction performance is increased as the complexity increases.

Finally, cross-validation is applied to the models that are considered after the upper steps. The cross-validation proves whether the considered models are capable of predicting the test data regardless of where the test data is selected. In this study, 5-fold cross-validation is performed and the final model is selected considering the cross-validation results.

Selected Models: In this section, statistical results for the models that are selected using he purposed methodology are presented. Two hidden layers are considered for modelling since the data at hand is highly nonlinear. The models that are used in the simulations are the ones with 50 nodes on hidden layers. The other models are considered to be capable, however, downgraded models compared to 50 – 50 ones.

Modeling results are evaluated by their statistical performance in terms of r^2 and MSE, physical modeling performance. Table 1 shows the statistical performance of technique on every coefficient in terms of r^2 and mean squared error. In addition, it should be noted that r^2 is a non-dimensional statistical metric, whereas MSE depends on the parameters' magnitude. Therefore, in Table 1, MSE of CM and CLN coefficients appear to have larger values unlike the other parameters.

Table 1. Selected model statistical performance comparison

R^2			
Coefficient	**50-50**	**30-30**	**10-10**
CX	0.9994	0.9990	0.9943
CY	0.9988	0.9986	0.9954
CZ	0.9995	0.9994	0.9970
CLL	0.9949	0.9919	0.9725
CM	0.9988	0.9978	0.9889
CLN	0.9975	0.9958	0.9846

MSE			
Coefficient	**50-50**	**30-30**	**10-10**
CX	0.0006	0.0011	0.0058
CY	0.0202	0.0278	0.0818
CZ	0.0127	0.0215	0.0823
CLL	0.0108	0.0184	0.0593
CM	0.4429	0.8664	4.0416
CLN	0.6067	1.0917	3.7103

The modelling results show that as the model complexity increases, the modeling performance follows along. Since the models are not validated by flight test, the 50 – 50 models are considered as the most accurate models at this point. 30 – 30 models are showing similar performance to 50 – 50 ones. However, 10 – 10 models have significantly lower performance at moment coefficients. Also additional investigation shows that the 10 – 10 models struggles to capture the information in the data for moment coefficients which is a sign of high complexity model requirement. Nevertheless, the models will be used for comparison purposes.

The variable importance results on coefficients are presented in Figure 9. Each parameter affects the aerodynamic coefficients in different amount. For instance, pitching moment coefficient (C_m) is mostly related with α, whereas side force coefficient (C_Y) is with β. Figure 9 shows the variable importance on all coefficients.

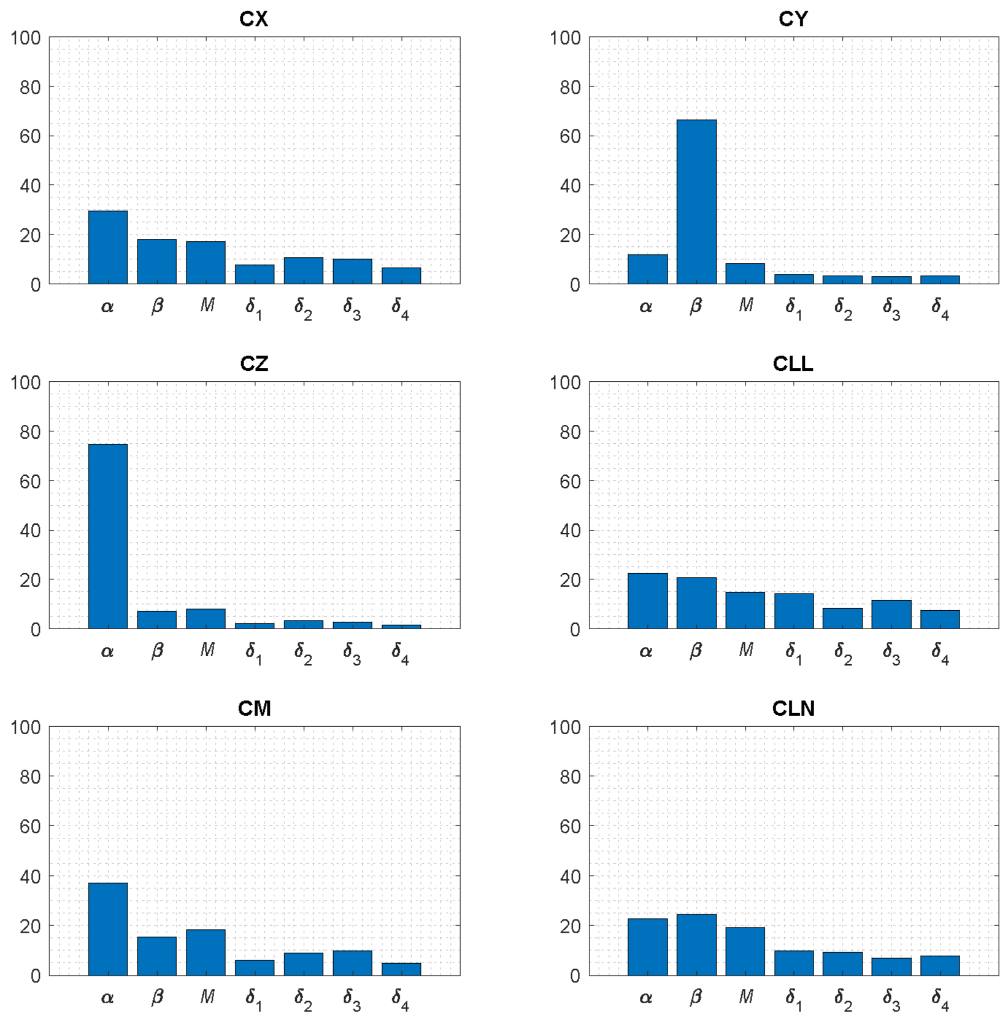

Figure 9. Variable importance check

SIMULATIONS

Three representative simulations that are conducted via 6DoF simulation environment are considered for this study. The simulations are conducted using the models with 50 – 50 nodes on 2 hidden layers which controller is also based on.

The scenarios generated as angle of attack biased (scenario 1), angle of sideslip biased (scenario 2). The last simulation excites both angle of attack and angle of sideslip. The selections are made to compare results for models with different complexity levels. Simulation results for flight variables are presented in Figure 10.

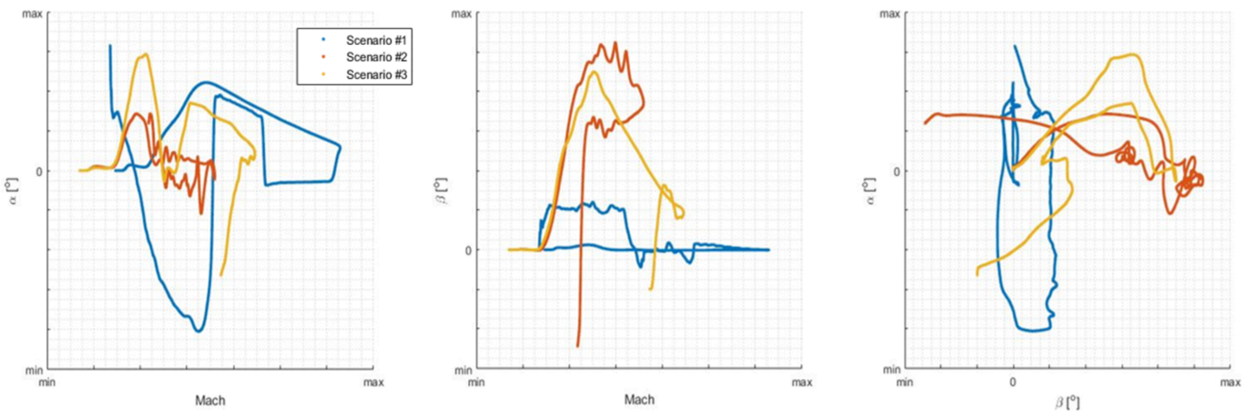

Figure 10. Simulation results

A. Model Result Comparisons

The results shown here are for simulations conducted with 50 – 50 models. The controller used for simulations is based on the 50 – 50 models. The variables collected from simulation results are fed to 10 – 10 and 30 - 30 models to generate the results presented below. This way, the response of the vehicle is not altered due to the model change.

As stated before, since the models are not validated by flight test, the 50 – 50 models are considered to be the most accurate models. Consequently, 50 – 50 models are considered as test bed and the results of remaining models are evaluated against 50 – 50 results.

The comparison results for three scenarios are presented below. The percent differences are calculated based on the interval of change for each coefficient.

Cm coefficient results for scenario 1 and for scenario 2 are given in Figure 11. As expected, in scenario 1, the 30 – 30 model result is relatively close to 50 – 50 models where the 10 – 10 results have large differences. In addition, it is clear that 10 – 10 models have as significant trend change from the other models at the middle of the scenario. Similarly, to scenario 1, in scenario 2, the 30 – 30 results have lower differences from the 50 – 50 models.

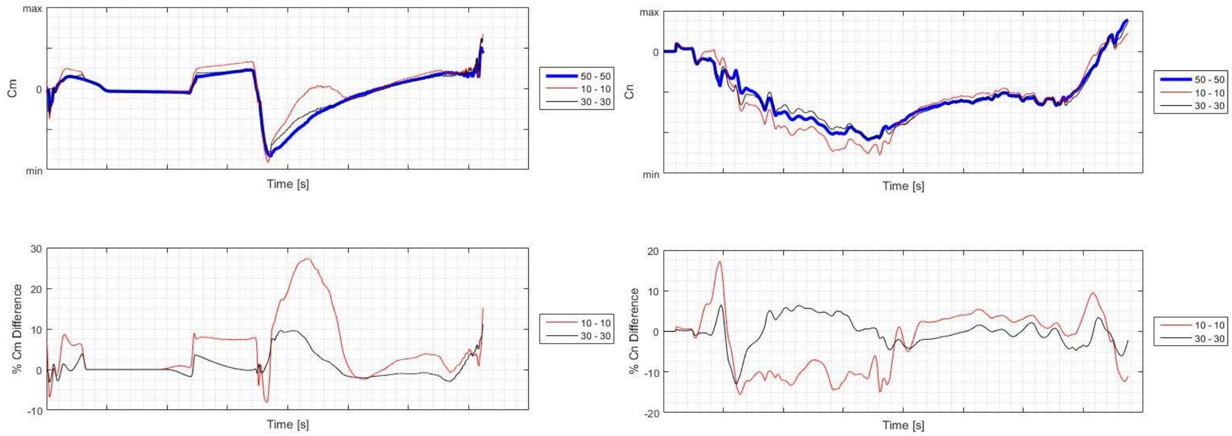

Figure 11. Scenario #1 (left) and #2 (right), model results comparisons

Finally, Cm and Cn coefficient results for scenario 3 is given in Figure 12. Overall, the 30 – 30 results have lower differences from the 50 – 50 models. However, the differences on Cn coefficient are larger compared to the scenario 2 results.

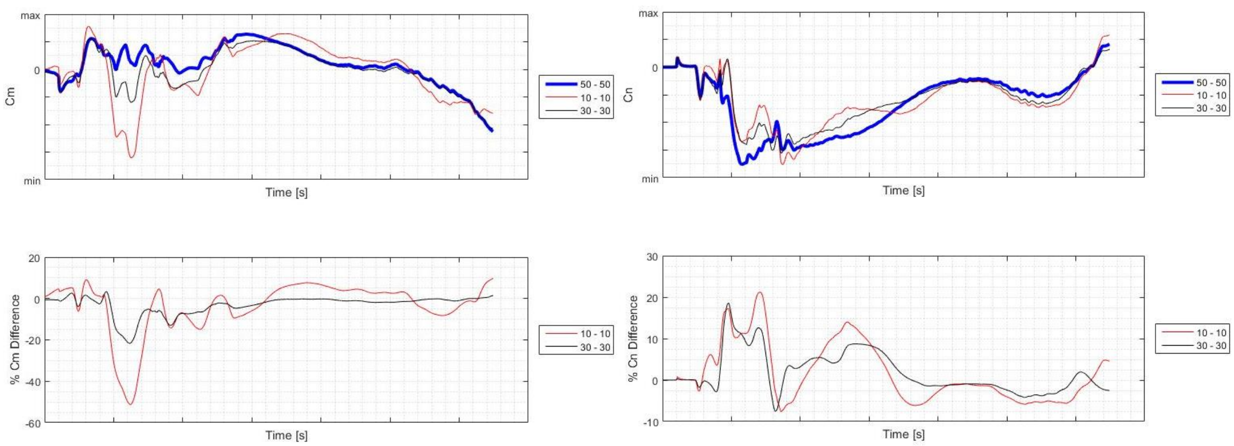

Figure 12. Scenario #3, model results comparisons

The comparison results are summarized in Table 2. Cl coefficient results are not presented since the coefficient is not excited properly during simulations and small differences results with large percentiles.

Table 2. 10 – 10 and 30 – 30 Model Results Summary

		10 - 10					**30 - 30**				
		CX	**CY**	**CZ**	**Cm**	**Cn**	**CX**	**CY**	**CZ**	**Cm**	**Cn**
Max. Absolute Difference [%]	**Scenario #1**	**14**	2	3	**27**	**26**	**16**	1	1	**11**	**9**
	Scenario #2	**27**	3	4	**16**	**17**	**18**	2	3	**18**	**13**
	Scenario #3	**28**	2	3	**51**	**21**	**18**	1	4	**22**	**19**
Mean Absolute Difference [%]	**Scenario #1**	2	0	1	6	5	3	0	0	2	2
	Scenario #2	10	1	2	7	6	3	1	1	6	3
	Scenario #3	6	1	1	8	5	2	0	1	3	4

For the force coefficients, the results show high differences for CX. The CX coefficient is highly nonlinear and very hard to model by nature. As a result, the high differences in this coefficient is not unexpected. The rest of the force coefficients have little differences with lower values for 30 – 30 models.

The moment coefficients however, have larger differences overall. The non-linear nature of the coefficients can be pointed out as the reason of this result. Normally, 10% of difference is not unexpected during modelling the moment coefficients for highly nonlinear aerodynamics with higher differences at certain extreme points. As can be seen from the results, the mean values of the differences are within 10% for 10 – 10 and 30 – 30 models. On the other hand, the maximum differences vary greatly between models with 10 – 10 models on the larger side. Both differences are significant but, the results for 10 – 10 models are very high.

The results show that with such nonlinearly behaving aerodynamics, the modelling complexity is a factor that effects how the models behave with same inputs. While the, models with close statistical performance behaves similarly, models with wide complexity gaps may result in unexpectedly different results. In that sense, 30 – 30 models can be considered as or low complexity alternative model to 50 – 50 models for robustness analysis. 10 – 10 models are far off to the 50 – 50 models and they are not recommended to be used for simulations. This result is not unexpected since the modelling results showed that the 10 – 10 models are struggling to capture the necessary information in moment coefficients as well.

B. Simulation Result Comparisons

In this section, the models that are presented above are used as the aerodynamic models for the simulations. The controller used is not altered. The one designed based on the 50 – 50 models is kept in use. Scenario 3 is selected as candidate since it excites both angle of attack and angle of sideslip at the same time. The results are presented in Figure 13.

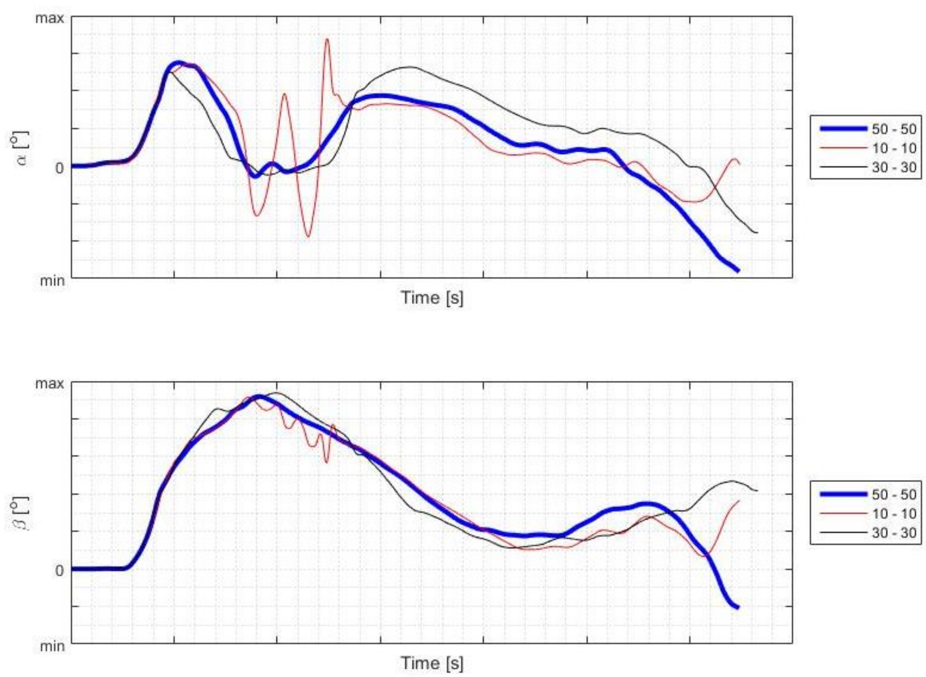

Figure 13. Scenario #3, simulation results comparison

Simulation results show that the controller is still able to function with the 30 – 30 models. On the other hand, it struggles on the middle part of the simulation for 10 – 10 models. It is clear that the 10 – 10 models are producing unexpected results for the controller to coop with which is expected as presented in the previous sections.

30 – 30 models simulation results are behaving similarly in trend with the 50 – 50 results, however, on the first maneuver two results are separating from each other. The separation is expected since the moment coefficients have a difference at the point as presented in the previous section. The rest of the simulation goes with a bias and the end part becomes separated since the trajectory difference due to the bias changes the requirement for the ending maneuver. Overall, the results are supporting the claim that the 30 – 30 can be considered as or low complexity alternative model to 50 – 50 models.

CONCLUSION

In this paper, an approach for design of experiment for wind tunnel testing and modeling of the collected aerodynamic data for an agile air vehicle is presented with a case study. The purpose is to improve the air vehicle's 6DoF simulation accuracy and performance by a good representation of the aerodynamics.

Wind tunnel tests are costly, as a result, one needs to optimize the number of test points at hand to obtain the maximum benefit. For this purpose, DoE is considered to determine the test matrix. DoE is a vast subject in statistics and there are lots of different algorithms. Among those different algorithms, sequential space filling is purposed and applied when designing the experiment. The benefit of this approach is that it enables the user to generate designs that can be implemented in multiple phase test campaigns.

For agile air vehicles, the dependency of aerodynamic coefficients on the flight variables are highly non-linear due to large flight envelope. An approach with ANN modeling technique, which is in common use in the field, is purposed and utilized to construct models to predict aerodynamic coefficients.

The purposed approach is applied to produce models with three complexity levels for each coefficient. Due to the fact that the aerodynamics has not validated with flight test yet, the highest complexity models are considered as the reference. The other models with lower complexity levels are compared to the reference model and evaluated.

The results show that reducing the complexity on force coefficients except CX does not have a major effect on the results since the nonlinearity is low on these coefficients. On the other hand, the moment coefficients are much more sensitive to changes.

Decreasing complexity mildly in moment coefficients can result in similar models to the high complexity one. Simulation results with similar trends and acceptable biases can be achieved. In addition, model results can be used in robustness analysis.

Decreasing the model complexity sharply results in a different way however. A model that struggles to capture the necessary information can result in unexpectedly high differences in simulations which mostly falls out of controller limits.

The study results show that the modelling of nonlinear aerodynamics is a challenge since even at the modelling stage, it can produce different results for simulation models. The controller design must have a certain allowance on the coefficient changes to coop with the actual airframe during flight. In addition, the final models must be validated with the flight test to reduce the risk of model variety. At the same time, the flight tests should ensure the accuracy of the simulations is improved or not.

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REFERENCES

Cook, M.V. (2007), Flight Dynamics Principles, Second Edition, Elsevier USA, 2007

Crombecq, K. and Dhaene, T. (2010), 'Generating Sequential Space-Filling Designs Using Genetic Algorithms and Monte Carlo Method', K. Deb et al. (Eds.): SEAL 2010, LNCS 6457, pp. 80–84, 2010.

Klein, V., Morelli, E.A. (2006), "Aircraft System Identification: Theory and Practice", AIAA Education Series, AIAA, 2006

Lo , C.F, Zhao , J.L. and DeLoach R (2000). Application of Neural Networks to Wind Tunnel Data Response Surface Methods, AIAA 2000-2639, 2000

Patel, N (2003), Data Mining, (Massachusetts Institute of Technology: MIT OpenCouseWare), http://ocw.mit.edu (Accessed October 10, 2017). License: Creative Commons BY-NC-SA

Savas, O., Topbas E., Unal, K., Karaca, H. D. and Kutay, A. T. (2018) "Experimental Design and Statistical Modelling Methodology for Wind Tunnel Aerodynamics of an Agile Missile to Improve the Simulation Accuracy and Performance" 2018 AIAA Modeling and Simulation Technologies Conference

Selvi S.T., Rama S., Mahendran E. (2007), ''Neural Network based Interpolation of Wind Tunnel Test Data'', IEEE 0-7695-3050-8/07, 2007

GENT University (2012), SUMO - SUrrogate MOdeling Lab, Retrieved 2012, http://sumo.intec.ugent.be/?q=SED