

Generating Aerodynamic Database from Closed Loop Simulated Flight Data

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Abstract

In designing flight control system or developing high-level flight simulator, the accurate and comprehensive representation of the aerodynamic characteristics of an aircraft is required. In case of high manoeuvrable unstable aircraft, the identification of the aerodynamic characteristics can be challenging because of the engaged control system. In this paper, it is aimed to estimate aerodynamics characteristics of highly manoeuvrable unstable aircraft with engaged control system for simulation data. For this purpose, F-16 nonlinear aircraft is modelled using aerodynamic database is derived from a low speed wind tunnel test. In analysis of simulated data, equation error and output error methods in time domain are used to estimate aerodynamic parameters defined in model postulate. The goal is to find a compact model structure which has adequate complexity to capture the nonlinearities. Using FAA specified guidelines in terms of tolerances on each variables for short-period and Dutch-roll manoeuvres, the identified model is validated.

1. Introduction

System identification yields a complete breakdown of the various components contributing to the observed response, and thereby provides an overall understanding of the flight vehicle's dynamics. For many applications, an aircraft can be assumed to be a rigid body, whose motion is governed by the laws of Newtonian physics. System identification can be used to characterize applied forces and moments acting on the aircraft that arise from aerodynamics, inertial, gravitational and propulsion. Typically, thrust forces and moments are obtained from ground tests, so aircraft system identification is applied to model the functional dependence of aerodynamic forces and moments on aircraft motion and control variables.

Aircraft system identification is primarily concerned with providing a mathematical description for the aerodynamic forces and moments in terms of relevant measurable quantities such as control surface deflection, aircraft angular velocity, airspeed or Mach number, and orientation of the aircraft to the relative wind [1]. Aerodynamic parameters quantify the functional dependence of the aerodynamic forces and moments on measurable quantities, when the mathematical model is parametric. The parameter estimation process consists of finding values of unknown model parameters in an assumed model structure.

The field of system identification is so wide that it is impossible to cover it in all aspects in such a paper. Briefly, parameter estimation can be seen as defining a probability density function describing the difference between system model response and measured system response. Two estimation approach can be distinguished from each other. Non state parameters such as force and moment coefficients, which are not integrated during simulation are determined without the knowledge of their past history. This method is called equation-error method [2]. System outputs are taken such as angle of attack, angular rates etc. which are integrated during a simulation and thus estimation approach is called output-error method [2]. In this study, equation-error method is used firstly to identify aerodynamic parameters and the results are used as starting point in output-error method for fine-tuning. Model postulation is created according to prior knowledge about aircraft aerodynamics.

The flight test data used in this study is collected from a nonlinear F-16 simulation. F-16 nonlinear aircraft is modelled with controls for leading edge flap, flaperon, elevator, rudder and throttle. Stability augmentation system and control

augmentation system have been developed using this nonlinear model to carry out the manoeuvres with safety. Simulation data is collected in 12 different trim points with combination of two different altitude and 6 different speed settings that differs from 0.3 Mach to 0.6 Mach speed. To excite the different modes of vehicle dynamic motion, control inputs of pilot are designed for short-period, Dutch-roll and bank-to-bank manoeuvres.

This study aims to address the challenges in system identification process and how to overcome them in a practical way. In this content, parameter estimation technique and analysis of parameter estimation for equation error and output error methods are described in detailed. Results are validated using FAA specified guidelines in terms of tolerances on each variable for short-period and Dutch-roll manoeuvres.

2. Aircraft Modelling

The aircraft simulation model includes the main model and subsystem models (bare-airframe, actuator, engine, environment, sensor and flight control). Bare-airframe model consists of aerodynamics and equation of motion models (EQM). The aerodynamic data of the aircraft are obtained from the study published in the 1979 NASA technical report prepared from wind tunnel tests [3]. In EQM model, all forces and moments acting on body axes is summed and equations of motion is solved. Actuators are modelled as a first order system [4]. Flight control model includes stability augmentation system (SAS) and control augmentation system (CAS). In highly manoeuvrable aircraft, CAS and SAS systems are needed to perform tasks such as precision tracking of targets [4]. Pitch rate command and roll rate command system is used to control the aircraft.

3. Simulation & Data Gathering

Estimation of stability and control derivatives are carried out primarily from the dynamic response of an aircraft to specific control inputs. A variety of manoeuvres is usually necessary to excite dynamic motion about different axes using independent inputs on every control. In general, it is recommended to start each manoeuvre from a trimmed level flight and allow about 5-10 seconds of steady flight before applying specific control inputs and depending upon the mode of motion, to allow sufficient time after the input to allow the aircraft oscillate [1].

3.1 Input design

The main idea behind system identification manoeuvres which will be described is to excite related modes of aircraft motion independently and sufficiently. In general, while exciting a particular mode, excitation of other modes should be minimized. Input design for short period mode, Dutch roll and bank to bank manoeuvres are explained in below.

Short Period Mode (SP);

It is a multi-step 3-2-1-1 elevator input exciting the short period motion with variations in the angle of attack of about 4 degrees and 0.5 g in the vertical acceleration. It provides the most information to enable the estimation of derivatives pertaining to the vertical and pitching motion [1].

Dutch Roll (DR);

The Dutch Roll manoeuvre provides information to enable the estimation of derivatives pertaining to the lateral motion[1]. The Dutch roll manoeuvre provides maximum information on the frequency and damping of this oscillatory mode. It is excited by applying rudder inputs. Usually several cycles of oscillations are recorded. The resulting maximum peak-to-peak variation in the angle of sideslip is typically of the order of ± 4 deg., or 0.1g lateral acceleration. Dutch roll and bank-to-bank manoeuvres are performed at different trim speeds, because most of the lateral –directional derivatives depend on the angle of attack.

Bank to Bank (BTB);

Bank to Bank manoeuvre provides more additional information on lateral-direction derivatives related to roll rate and aileron deflection [1]. Aileron input is applied, which roll the aircraft from wings-level to 30 deg. bank on one side; this is followed by changing input and going smoothly to wings-level and to opposite bank angle; and again to wings-level condition. The changes in aileron result in rapid variation in roll rate and acceleration.

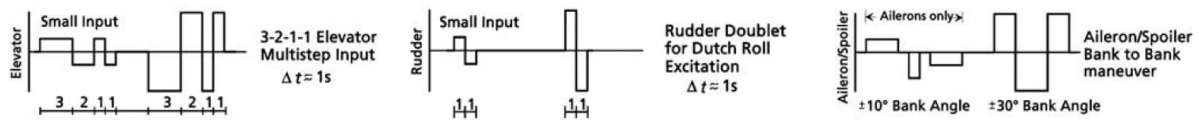


Figure 1: Manoeuvre Excitation for Short Period, Dutch-Roll, Bank to bank [1]

3.2 Simulations

Simulation data is collected in 12 different trim points with combination of two different altitude and 6 different speed settings that differs from 0.3 Mach to 0.6 Mach speed. To excite the different modes of vehicle dynamic motion, control inputs of pilot are applied for short-period, Dutch-roll and bank-to-bank manoeuvres. All test steps were started at trim condition and after the manoeuvre the autopilot was activated to trim the aircraft.

For aerodynamic model extraction from test data, a typical set of measurements required consists of 1) control surface deflections, 2) linear accelerations, 3) angular rates, 4) attitude angles, 5) air data, 6) static pressure, 7) engine parameters, and 8) pilot forces are recorded [1, 2]. A sampling frequency of 20-25 Hz is usually sufficient for rigid-body aerodynamic model estimation [2]. Therefore, simulation results are recorded at 20 Hz sampling rate.

4. Flight Path Reconstruction

Flight path reconstruction (FPR) is needed to improve flight test data (measured data) because LS methods are so sensitive to such systematic errors (Scale factor, Zero shift biases) [1]. Flight path reconstruction is also called as data compatibility check. The aim of data compatibility check is to ensure that measurements used for aerodynamic model identification are consistent and error free. The basis for verifying the compatibility of measured data is the use of kinematic relationships.

In simulations, systematic errors such as scale factor and zero shift biases not included. Therefore, FPR process is not needed. If there is a systematic error in data, flight path reconstruction process of flight data can be handled in two steps described in below [1].

- Scale factor and zero shift bias values are determined using output error method.
- After scale factor and bias values are cleared from data, aircraft state estimation is done to check the compatibility of measured values.

5. Model Postulation

Modelling the aircraft aerodynamics raises the fundamental question of what the mathematical structure of the model should be. Aerodynamic modelling, which provides a means of obtaining relationships between the three forces X, Y, Z along the three Cartesian coordinates and the moments L, M, N about these axes as functions of the linear translational motion variables u, v, w, rotational rates p, q, r and control surface deflections [2]. For system identification applied to aircraft, it is more convenient to use non-dimensional derivatives of the non-dimensional aerodynamic force and moment coefficients CX, CY, CZ, Cl, Cm, and Cn. These derivatives are obtained from the following relationships

Longitudinal aerodynamic coefficients:

$$C_a = C_a(\alpha, \beta, q, \delta_e, C_T) \text{ for } a = D, L \text{ and } m$$

Lateral aerodynamic coefficients:

$$C_a = C_a(\alpha, \beta, p, r, \delta_a, \delta_r, C_T) \text{ for } a = Y, l \text{ and } n$$

When the broad range of aircraft flight envelope is considered, these aerodynamics coefficients have nonlinear relationships with their dependent variables. The nonlinearity in model postulation can be expressed with using polynomial function or using breakpoints. Parameters dependent on angle of attack in longitudinal coefficients are expressed with breakpoints.

$$\begin{aligned}
C_X &= C_{X0} + C_{X\alpha}(\alpha) + C_{X\delta_e}(\delta_e, \alpha) + C_{Xq}q + C_{X\delta_{LEF}}(\delta_{LEF}, \alpha) \\
C_Z &= C_{Z0} + C_{Z\alpha}(\alpha) + C_{Z\delta_e}(\delta_e, \alpha) + C_{Zq}q + C_{Z\delta_{LEF}}(\delta_{LEF}, \alpha) \\
C_m &= C_{m0} + C_{m\alpha}(\alpha) + C_{mq}q^* + C_{m\delta_e}(\delta_e, \alpha) + C_{m\delta_{LEF}}(\delta_{LEF}, \alpha) \\
C_Y &= C_{Y0} + C_{Y\beta}(\alpha, \beta, \beta^3) + C_{Y\delta_a}(\delta_a, \beta) + C_{Y\delta_r}(\delta_r, \beta) + C_{Yp}p^* + C_{Yr}r^* + C_{Y\delta_{LEF}}\delta_{LEF} \\
C_l &= C_{l0} + C_{l\beta}(\alpha, \beta, \beta^3) + C_{l\delta_r}(\delta_r, \beta) + C_{l\delta_a}(\delta_a, \beta) + C_{lp}p^* + C_{lr}r^* + C_{l\delta_{LEF}}\delta_{LEF} \\
C_n &= C_{n0} + C_{n\beta}(\alpha, \beta, \beta^3) + C_{n\delta_r}(\delta_r, \beta) + C_{n\delta_a}(\delta_a, \beta) + C_{np}p^* + C_{nr}r^* + C_{n\delta_{LEF}}\delta_{LEF}
\end{aligned}$$

Where normalized angular velocities are;

$$p^* = \frac{pb}{V}; q^* = \frac{ql}{V}; r^* = \frac{rb}{V}$$

6. Parameter Identification Methodology

To estimate aerodynamic parameters defined in model postulate, equation error and output error methods in time domain are used in analysis of simulated data. Equation-error method is used firstly to identify aerodynamic parameters and the results are used as starting point in output-error method for fine-tuning. For both methods, FVSysID software developed by Jategaonkar Ravindra is used [8].

6.1 Equation error method

The equation-error method was one of the first analytical techniques used to estimate aircraft dynamic model parameters from flight data. The equation-error method can be considered a method wherein the model matches state time-derivative information from the dynamic system, rather than matching the states or outputs. There is no need to integrate equations of motion to get model outputs when using the equation-error method, because the matching is done in the equations of motion themselves (hence the name “equation-error”). One important practical consequence is that the equation-error method can be applied equally well to data from inherently unstable aircraft flying under closed-loop feedback control [1, 5].

In its most common form, the equation-error method calculates aerodynamic parameter estimates that minimize the sum of squared differences between values of non-dimensional force and moment coefficients determined from measured flight data and corresponding model values. The non-dimensional force and moment coefficients are computed by substituting measured and known quantities.

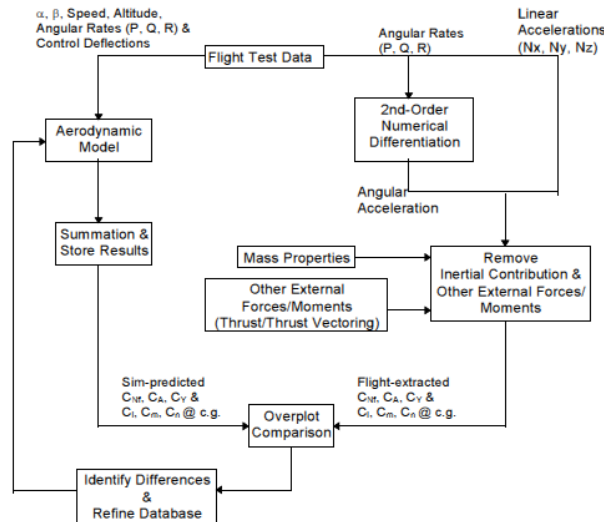


Figure 2: Flowchart of equation error method

The general form of model equation and least equation can be written using vector and matrix notation as

$$y = X\theta$$

And;

$$z = X\theta + v$$

Where;

$$z = [z(1) \ z(2) \ \dots \ z(N)]^T = Nx1 \text{ vector}$$

$$\theta = [\theta_0 \ \theta_1 \ \dots \ \theta_n]^T = n_p x1 \text{ vector of unknown parameters, } n_p = n + 1$$

$$X = [1 \ \xi_1 \ \dots \ \xi_n]^T = Nx n_p \text{ vectors of ones and regressors}$$

$$v = [v(1) \ v(2) \ \dots \ v(N)]^T = Nx1 \text{ vector of measurement errors}$$

The regressors vectors $\xi_j, j = 1, 2, \dots, n$ are known postulated functions of the vectors of independent variables. The best estimator of θ in a least square sense comes from minimizing the sum of squared differences between the measurement and the model,

$$v = z - X\theta$$

$$J(\theta) = \frac{1}{2}(z - X\theta)^T(z - X\theta)$$

The parameter estimate $\hat{\theta}$ that minimizes the cost function $J(\theta)$ must satisfy

$$\frac{\partial J}{\partial \theta} = -X^T z + X^T X \hat{\theta} = 0$$

Or

$$X^T X \hat{\theta} = X^T z$$

The $n_p = n + 1$ equations represented in equations above are called the normal equations. The solution of these equations for the unknown parameter vector θ gives the formula for the least square estimator, also called the ordinary least squares estimator,

$$\hat{\theta} = (X^T X)^{-1} X^T z$$

The equations above show that the equation-error method for parameter estimation has a relatively simple, non-iterative solution, based on linear algebra. The equation-error method can be used very efficiently for very large data sets, e.g., from wind tunnel tests or multiple flight test manoeuvres.

Some properties of equation error method can be summarized as:

- EEM minimizes the equation error between measured and estimated dependent variables
- Presents a single shot solution, no iterations required
- Easy to implement, involves simple matrix operations
- Preferred for linear and unstable system

6.2 Output error method

The output-error method can be considered a method wherein the model matches the states or outputs from the dynamic system. A model that uses equation error parameter estimates will not produce the best match to the measured outputs of the dynamic system, since that is not what is being optimized. Any mismatch of the equation-error model to the (derivative) data will be integrated over time and numerical integration of inherently unstable and highly sensitive systems may lead to numerical divergence in the simulation and optimization. Unless the modelling errors from the equation-error parameter estimation are low-amplitude and zero-mean, the result can be a significant mismatch between measured aircraft outputs and the model outputs computed from the equations of motion using equation-error parameters. In the output-error case, the mismatch between measured outputs and model outputs is intentionally minimized by adjusting the parameter estimates. Since its introduction in the 1960s, the output error method is the most widely applied time-domain method to estimate aircraft parameters from flight data [1].

$$\dot{x}(t) = f[x(t), u(t), \theta], x(t_0) = x_0$$

$$y(t) = g[x(t), u(t), \theta]$$

$$z(t_k) = y(t_k) + Gv(t_k)$$

f and g are assumed to be real – valued

x : state variables

u : control variables

y : output variables

z : measured variables

$v(t_k)$: measurement error

θ : unknown variables

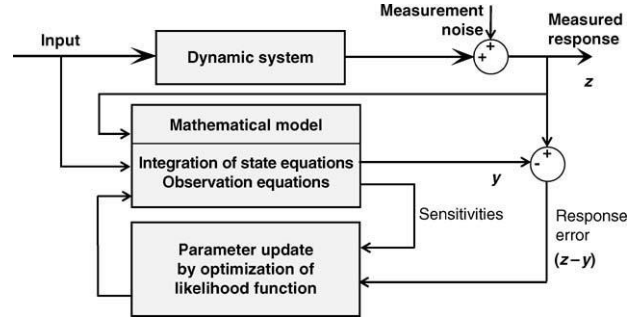


Figure 3: Flowchart of output error method [1]

Estimates of parameter vector $\hat{\theta}$ is obtained on minimizing the cost function

$$J(\theta, R) = \frac{1}{2} \sum_{k=1}^N [z(t_k) - y(t_k)]^T R^{-1} [z(t_k) - y(t_k)]$$

Where R is the measurement noise covariance matrix, given by

$$R = \frac{1}{N} \sum_{k=1}^N [z(t_k) - y(t_k)][z(t_k) - y(t_k)]^T$$

Updating of parameters is given by Gauss Newton formulation

$$\begin{aligned} \hat{\theta}_{k+1} &= \hat{\theta}_k + \Delta\theta \\ F \Delta\theta &= -G \end{aligned}$$

Where

$$\begin{aligned} F &= \sum_{k=1}^N \left[\frac{\partial y(t_k)}{\partial \theta} \right]^T R^{-1} \left[\frac{\partial y(t_k)}{\partial \theta} \right] \\ G &= - \sum_{k=1}^N \left[\frac{\partial y(t_k)}{\partial \theta} \right]^T R^{-1} [z(t_k) - y(t_k)] \end{aligned}$$

F is the information matrix (also called Hessian), G is the gradient vector and $\Delta\theta$ the parameter change vector.

6.3 Parameter estimation techniques

In parameter estimation, we use different sequence of manoeuvres to estimate each aerodynamic coefficients. These techniques are similar in itself for both longitudinal and lateral coefficients. Therefore, this procedure will be explained only for CZ force coefficient and CN moment coefficient as an example. Often there is a desire to estimate aerodynamic model parameters using data from more than one flight test manoeuvre. This is useful when individual manoeuvres have good information content for estimating some parameters but not others. Sometimes multiple manoeuvres taken together can provide more complete information for parameter estimation. Equation-error allows concatenation of the data from various manoeuvres [7, 8].

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Estimation of CZ coefficient (Longitudinal coefficient);

- 1) Use SP manoeuvres and estimate longitudinal parameters (*CL Postulate ver1*)
- 2) Try to find model-update to improve SP observing the time history plots, cross plots and cross plots of residuals, (*CL Postulate ver2*)
- 3) Free all parameters in *CL Postulate ver2* and reestimate parameters running SP+DR manoeuvres
- 4) Try to find model-update to improve DR observing the time history plots, cross plots and cross plots of residuals (*CL Postulate ver3*)
- 5) Free all parameters in *CL Postulate ver3* and reestimate parameters running SP+DR+BTB manoeuvres
- 6) Try to find model-update to improve BTB observing the time history plots, cross plots and cross plots of residuals (*CL Postulate ver4*)
- 7) Check cost function in all steps until change of cost function is small

Estimation of CN coefficient (Lateral coefficient);

- 1) Use DR+BTB manoeuvres and estimate parameters with (*CN Postulate ver1*)
- 2) Try to find model-update to improve DR+BTB observing the time history plots, cross plots and cross plots of residuals, (*CN Postulate ver2*)
- 3) Check cost function in all steps until change of cost function is small

6.4 Analysis of parameter estimation

Estimates are not the same as the facts. Model validation is necessary to gain confidence in, or reject, a particular model. This basic fundamental principle applies to all engineering decisions. In this section, we deal with the issues related to the process of determining correctness, accuracy and applicability of the identified model. The various different aspects of model validation can be broadly classified for equation-error and output-error methods.

Some of the criteria used in the equation-error method are as follows.

Statistical Accuracy; we firstly check if the expected value is reasonable. The magnitude of order must be close to real value. Otherwise, we are doing something wrong. And then we check the standard deviation, relative standard deviation and correlation matrix results. If relative standard deviation should not exceed 50 and none of correlation should exceed 0.9.

Time History Plots; comparing the time histories of flight measured and model estimated responses is a standard procedure to qualitatively evaluate the model fidelity. Any discrepancies in the match between the two responses often provide important clues to improve upon the model fidelity.

Cross Plots; besides plotting time histories of flight measured and estimated responses, it is sometimes necessary to make cross plots of arbitrary two variables, for example lift coefficient versus angle of attack, Rolling and yawing moment coefficients versus angle of sideslip, coefficient of drag versus lift coefficient. Such cross plots are useful to gain further insight into the modelling aspects.

Cross Plots of Residuals; the test of the residuals (error between the predicted and measured response) is a good indicator of the assumptions made. Flat spread of residual centered around zero is the ideal case whereas non-flat spread indicates that the model needs improvement with the variable observed.

Proof-of-match process is used in the output-error method.

Proof-of-Match (POM);

The capability of identified model is determined by comparing the flight measured system responses with those predicted by the model for the same ('identical') control inputs. In flight vehicle applications terminology, this process

is called proof-of-match; it is an important part of flight simulator certification and acceptance. In this proof-of-match process, the identified aerodynamic model is kept fixed[1].

A fundamental principle of empirical sciences suggests that complementary flight data , flight manoeuvres not used in the estimation of the aerodynamic database in equation error method, to check the model capability.

The FAA has also set out guidelines in their CFR (Code of Federal Regulations) FAR (Federal Aviation Regulation) Part 60 (FAA, 2008), which defines the requirements for the evaluation, qualification and also maintenance of FSTDs. The document includes six appendices covering requirements, objective tests for full flight simulators, subjective evaluation, sample documents, wind shear training and FSTD directives. [9]

The simulation is to be started from the same initial conditions as in the flight. The initial conditions have to be suitably adjusted to match the flight conditions to be adjusted. In real flight test, measurements of the control inputs and outputs are subjected to measurement errors and noise. They also have to be adjusted. Likewise, the identified models are not precise. That is why, aerodynamic coefficients also should be adjusted. A pragmatic approach is to allow small biases on the selected initial conditions, on the measured control deflections and on the aerodynamic coefficients. The effective aerodynamic parameters in system identification manoeuvres are listed below.

Table 1: The effective aerodynamic parameters in system identification manoeuvres

TEST	EFFECTIVE PARAMETER
SHORT PERIOD	CMAOA, CMQ
LONGITUDINAL STATIC STABILITY	CLAOA, CMAOA, CMDE, CMO
DUTCH ROLL	CNBETA, CNR, CNRUD
BANK TO BANK	Small <u>Amplitude</u> : CRDA, CRP High <u>Amplitude</u> : CNDA, CNP

To eliminate subjective evaluation of the match between measured system responses and model predicted outputs, FAA has specified guidelines in terms of tolerances for each variable, depending upon the nature of the validation test. As an example, Table 2 provides the definition of three tests, giving tolerances, flight conditions to be tested for each. For complete list of validation test, the reader is referred to [9, 10].

Table 2: FAA validation tests and tolerance values

Test Number	Test Title	Tolerance	Flight Condition
2.c.10	Short Period Dynamics	±1.5deg ±2 deg/sec 0.1 g	PITCH ANGLE PITCH RATE NORMAL ACCELERATION CRUISE
2.d.7	<u>Dutch Roll</u>	±2 deg/sec ±2 deg/sec 0.1 g ±1.5deg	ROLL RATE YAW RATE LATERAL ACCELERATION SIDESLIP ANGLE a) CRUISE b) APPROACH or LANDING
2.d.2 2.d.3	Bank To Bank	±2 deg/sec ±2 deg/sec 0.1 g ±1.5deg ±2 deg or ±%10 BANK ANGLE	ROLL RATE YAW RATE LATERAL ACCELERATION SIDESLIP ANGLE a) CRUISE b) APPROACH or LANDING

7. Parameter Identification Results

Firstly, equation error method is used to estimate parameters defined in model postulation. Parameter estimation technique given in previous section is applied in equation error method. After parameters are found, the results are used as starting point in output error method. Details for both results are explained here.

7.1 Equation error method

In equation error method, parameter estimation is done for all aerodynamic coefficient given in model postulate. However, results are given for only CZ force coefficient and CN moment coefficient.

7.1.1 CZ coefficient results

Simulation data of short period manoeuvres is used to estimate the parameters of CZ coefficient. The variables to which the CZ coefficient depends are determined in the model postulation study. Considering the nonlinear behaviour of the CZ coefficient depending on the angle of attack, the parameters depending on the angle of attack are represented with breakpoints.

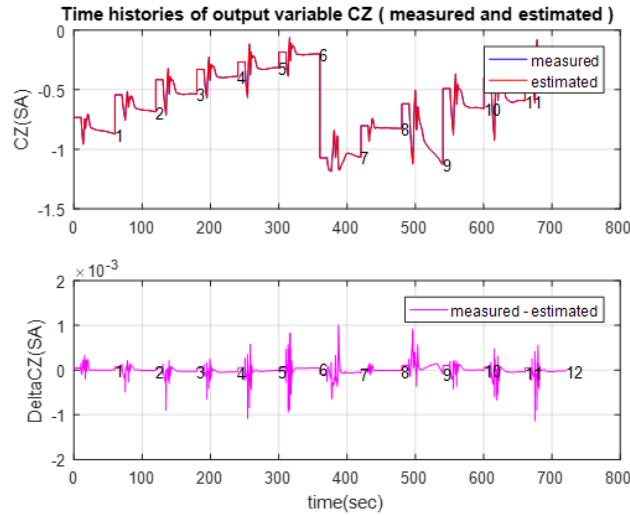


Figure 4: Time-dependent change of the measured and estimated CZ coefficient for clean data

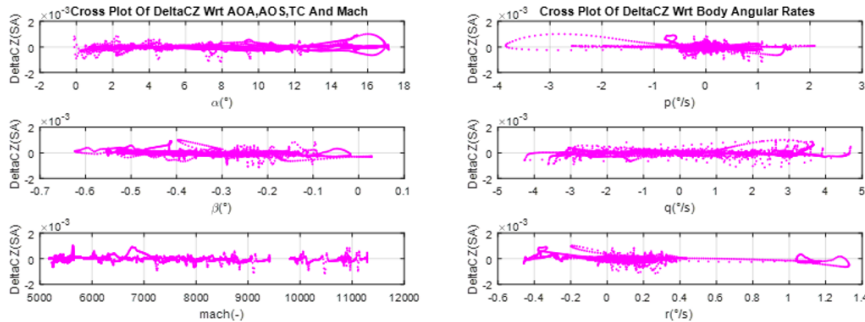


Figure 5 Time-dependent change of the measured and estimated CZ coefficient for clean data

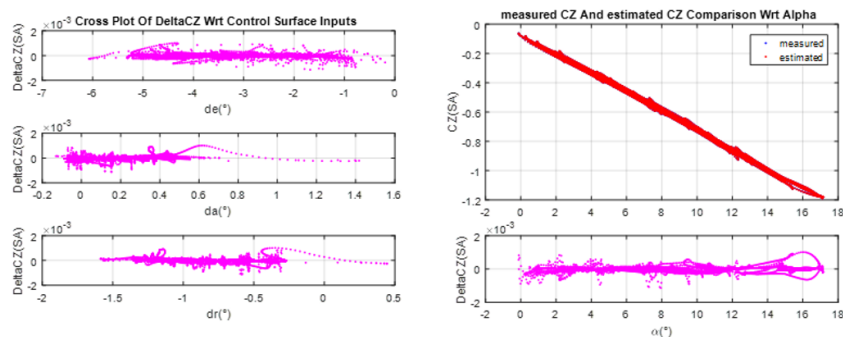


Figure 6: Time-dependent change of the measured and estimated CZ coefficient for clean data

When the changes in CZ coefficient $\delta_{LEF} - \alpha, \delta_e - \alpha, q - \alpha$ variables are considered, it is seen that the estimated values in the flight regime where the data are collected are similar to the actual values.

7.1.2 CN coefficient results

Simulation data of bank to bank and Dutch roll manoeuvres is used to estimate the parameters of CN coefficient. The variables to which the CN coefficient depends are determined in the model postulation study. The variables β , α , p , r , δ_a , δ_r ve δ_{LEF} appear to be effective in the CN coefficient. Considering the sideslip angle dependent behavior of the CN coefficient, a third-degree polynomial approach was performed for the sideslip angle dependent parameters.

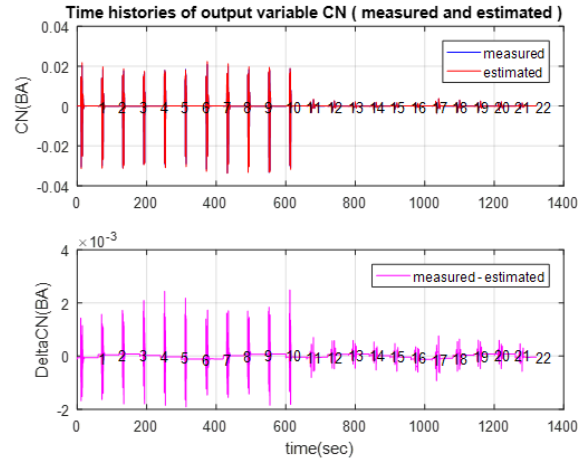


Figure 7: Time-dependent change of the measured and estimated CN coefficient for clean data

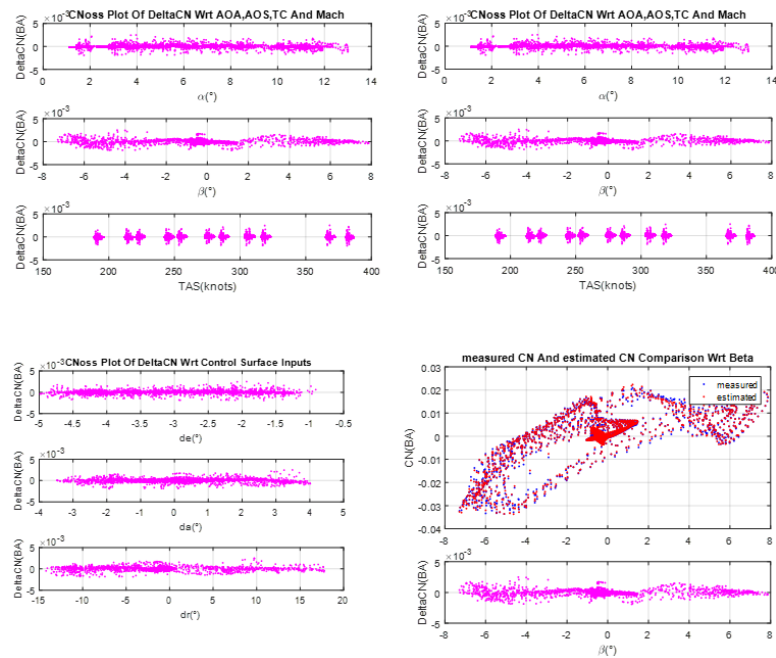


Figure 8: Variation of estimation errors according to dependent variables of CN coefficient for clean data

When the changes in CN coefficient $\delta_a - \beta$, $\beta - \alpha$, $r - \alpha$, $\delta_r - \alpha$, $\delta_r - \beta$, $\delta_{LEF} - \alpha$ and $p - \alpha$ variables are considered, it is seen that the estimated values in the flight regime where the data are collected are similar to the actual values. Only the variation of the dynamic stability coefficients at high attack angles and the LEF effects are not fully obtained by this postulate. The reason for this is that as the angle of attack increases, the nonlinear effects of the variables dependent on CN increase. Nonlinear behaviour depending on the angle of attack can be better expressed using breakpoints.

7.2 Output error method

Using the result obtained in equation error method as a starting point in the output method and keeping the aerodynamic model fixed in a complementary flight data and without any biases in the control deflections and in the initial conditions, we get the following results for a short period manoeuvre at 0.35 Mach and 10000 ft.

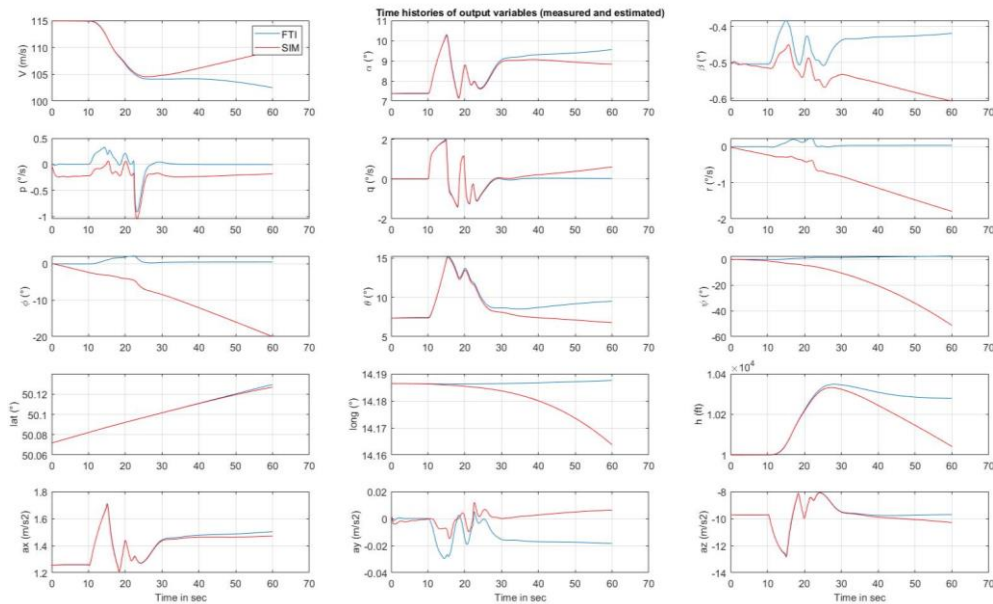


Figure 9: Time histories of output variables (measured and estimated)

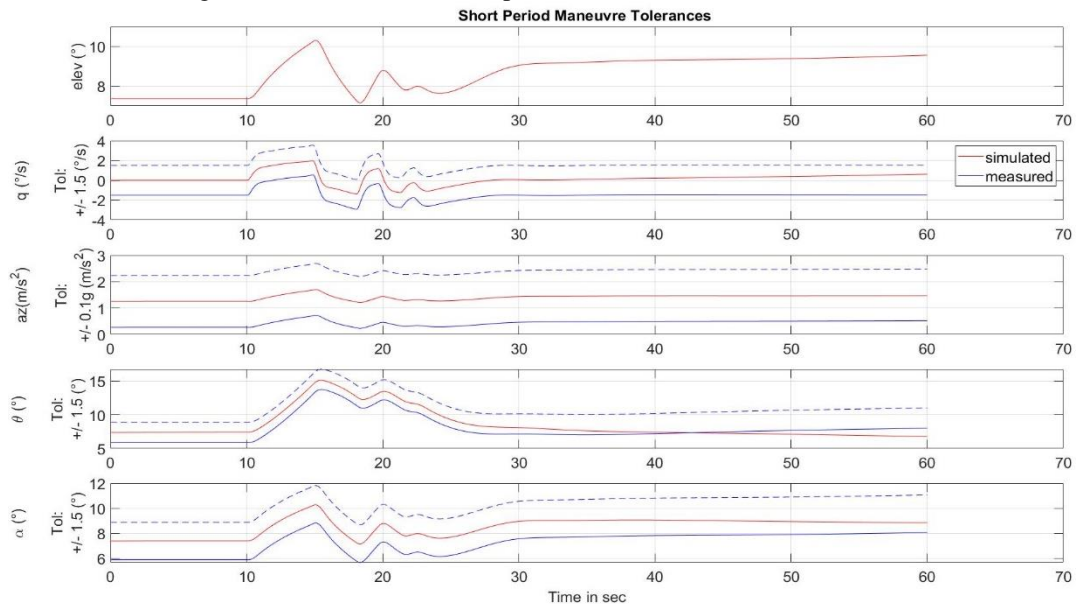


Figure 10: Short period manoeuvre tolerances

The flight measurements with these tolerances define a band within which the model predicted response must lie. For the other variables, particularly those of the cross axis, a qualitative match which means showing correct trends, is usually considered adequate. The model adequacy is quite apparent from the figure. The result is fairly good. There is just a small duration violation at pitch angle value for FAA requirements at figure (10).

Just recall that a pragmatic approach is to allow small biases on the selected initial conditions, on the measured control deflections and on the aerodynamic coefficients.

It is apparent that the specified initial conditions are reasonably accurate, but the simulation shows drifts in all of the variables that are attributed to biases in the control deflections and small errors in the starting values of the initial

conditions. Here, biases in the control deflections need to always be considered to avoid drifts in the integrated variables, even when such biases may be very small. After considering biases in the aileron deflection, there is a good match between measured data and simulated data at figure (11, 12) and we did not need to tune aerodynamic coefficients.

In case we need to tune aerodynamic coefficients, we do it from multiple short period manoeuvres by keeping C_{m_0} , $C_{m_{al}}$ and C_{m_q} parameters free (Table 1).

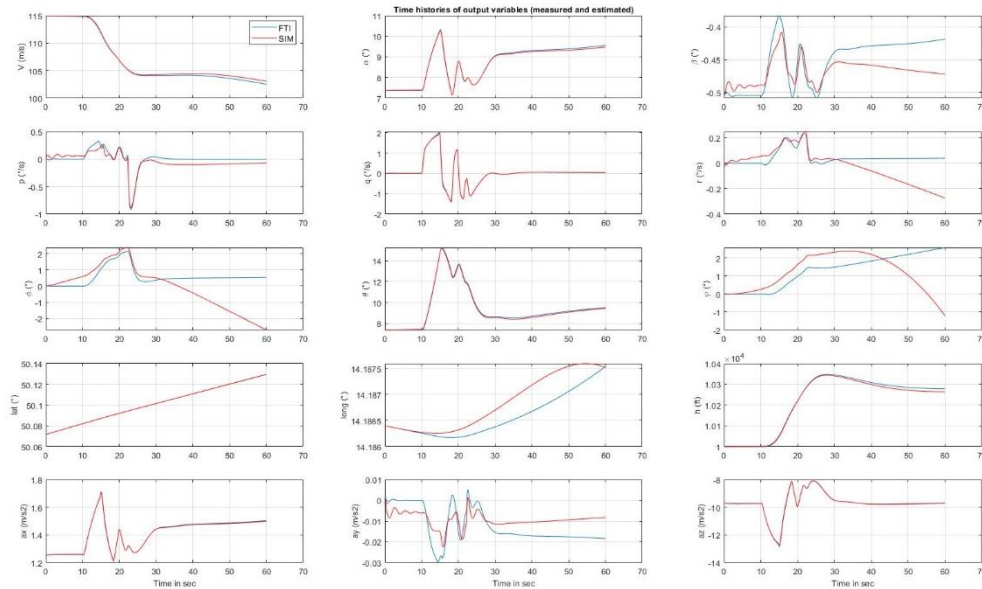


Figure 11: Time histories of output variables (measured and estimated)

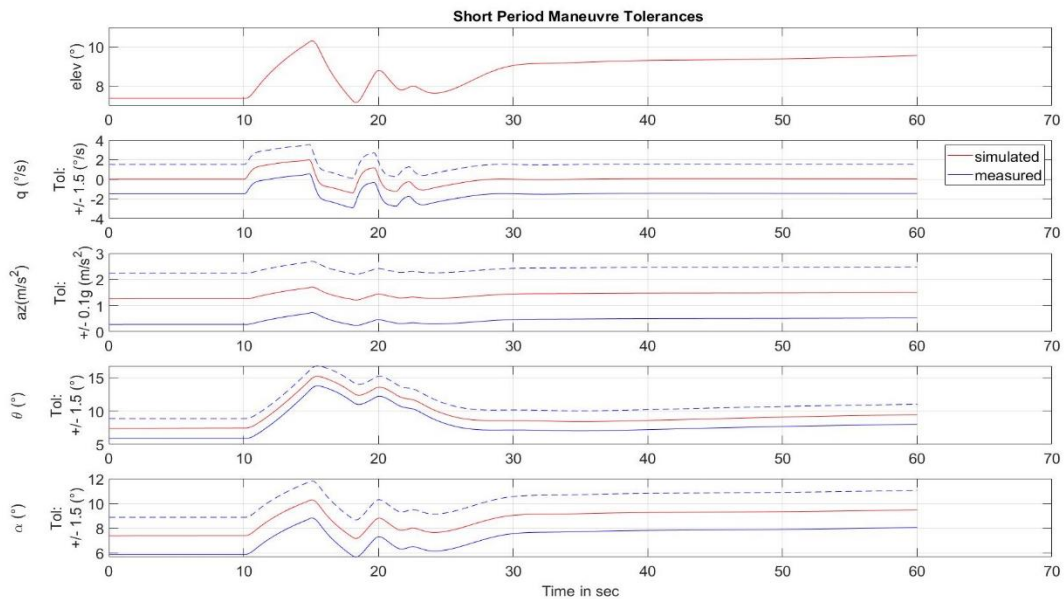


Figure 12: Short period manoeuvre tolerances

The dashed lines are obtained from measured data plus/minus the tolerances specified in table 1, and the continuous lines show the model predicted output, which is well within the allowed band for Level-D model fidelity.

And we get the following results for a Dutch-roll manoeuvre at 0.35 Mach and 10000 ft.

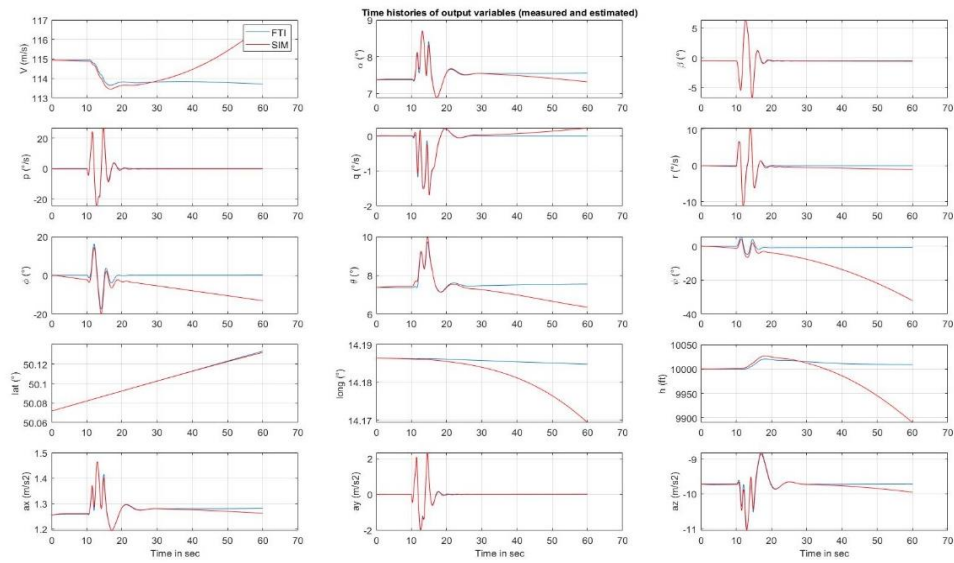


Figure 13: Time histories of output variables (measured and estimated)

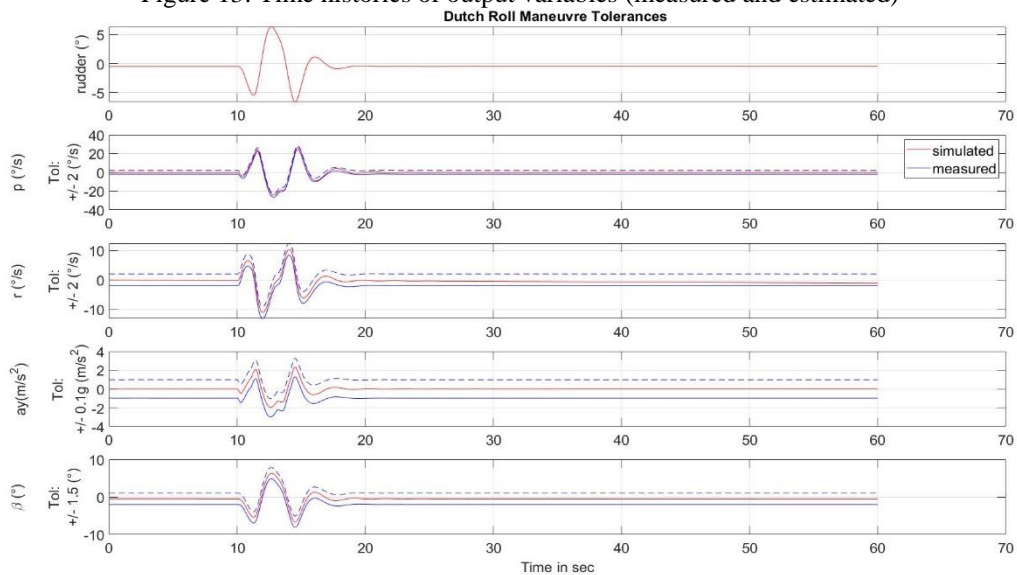


Figure 14: Dutch roll manoeuvre tolerances

Model predicted output is within the allowed band for Level-D model fidelity. But there are some drifts in the off axis variables such as velocity, altitude and bank angle etc. To avoid these drifts, we just add biases on aileron and elevator control surfaces and we get the following results.

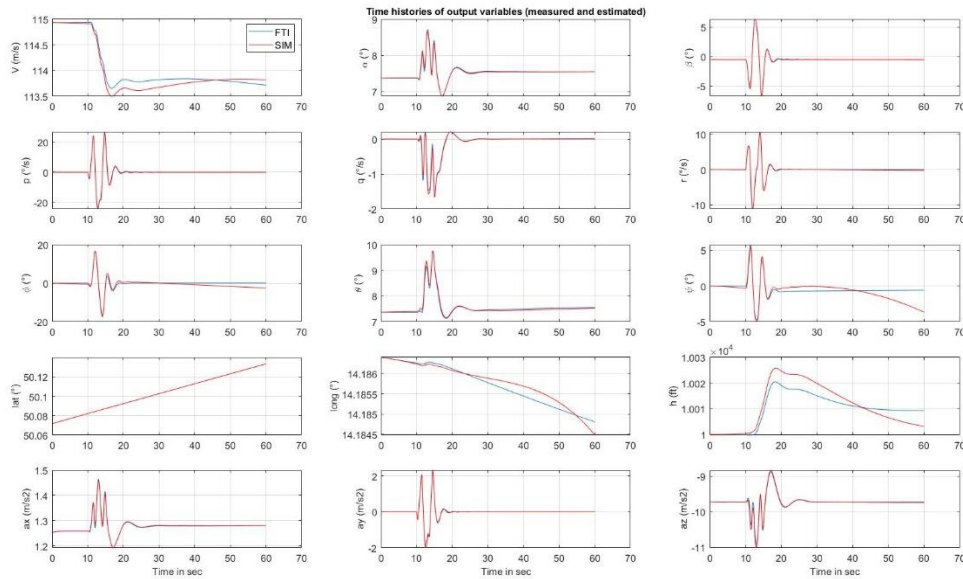


Figure 15: Time histories of output variables (measured and estimated)

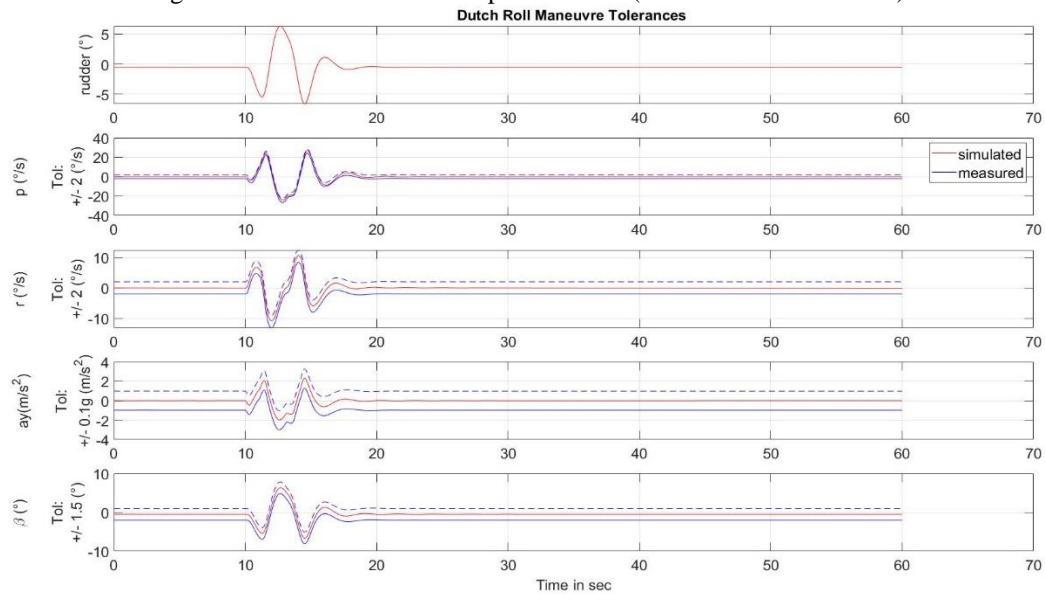


Figure 16: Dutch roll manoeuvre tolerances

8. Conclusion

The results showed that model predicted output is within the allowed band for FAA tolerances when keeping the aerodynamic model fixed and just adding some small biases on control surfaces. It means that the aerodynamic model which is generated by Equation Error Method is quite well.

References

- [1] Jategaonkar R., Flight Vehicle System Identification: A Time Domain Methodology ,AIAA, Reston, Virginia,2006
- [2] Klein, V. and Morelli, E.A Aircraft System Identification – Theory and Practices, AIAA Education Series, AIAA, Reston, VA, 2006
- [3] Nguyen, L. and Ogburn, M., Simulator Study of Stall/PostStall Characteristics of a Fighter Airplane with Relaxed Longitudinal Static Stability. NASA Technical Paper 1538. 1979
- [4] Stevens, B., Lewis, F., Johnson, E. Aircraft Control and Simulation Dynamics, Controls Design and Autonomous Systems.2016
- [5] Jategaonkar, R.V..and Thielecke, F. Evaluation of Parameter Estimation Methods for Unstable Aircraft. Journal of Aircraft. 1994.
- [6] FVSysID SOFTWARE by Ravindra Jategaonkar
- [7] Ozger,E., ‘Introducing a Combined Equation/Output Error Approach in Parameter Estimation’, AIAA, 2010
- [8] Morelli, E. A., ‘Practical Aspects of the Equation-Error Method for Aircraft Parameter Estimation’, AIAA, 2006
- [9] FAA (2008) 14 CFR FAR Part 60, Requirements for the Evaluation, Qualification and Maintenance of Flight Simulation Training Devices, Federal Aviation Administration
- [10]RAeS (2005) Flight Simulator Evaluation Handbook, vol. 1, 3rd edn, Royal Aeronautical Society, London