Identification of Aircraft Parameters in the Lateral-Directional Flight Dimension with Variation of Control Input

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Abstract

In this research, identifying aircraft parameters is carried out for the lateral-directional dimension by noticing the variations of the given control surface deflection input. The inputs are pulse, doublet, and 3-2-1-1. Among the input forms, it is not known which state is most suitable for the lateral-directional dimension. Therefore simulation is done by varying the input deflection control surface and simulation time. The input given is a deflection of the aileron and rudder control surfaces. The purpose of this research is to identify the most suitable input for identifying parameters in the lateral-directional dimension using the equation error method with the ordinary least square estimation technique and to observe the effect of simulation time. The aircraft used is the Lockheed C-5 Galaxy. The simulation results show that the combination of the 3-2-1-1 input form in the aileron deflection surface and the input pulse shape on the Rudder has an error value of about 0.365. This value is smaller among all cases seen from the error matrix A. Based on that, the combination of two inputs is the most suitable for the lateral-directional dimension than the other inputs that have been given.

Keywords*: aircraft; identification of parameters; model; input variations; lateral-directional.*

Nomenclature

y_v	=	The Partial derivative of the side force Y to the side force variable v, 1/s
y_P	=	The Partial derivative of side force Y to rolling rate variable p, -
y_r	=	The Partial derivative of side force Y to rate variable yaw r, m/s
y_ϕ	=	The Partial derivative of side force Y to roll angle variable ϕ, m/s^2
$y_{\delta a}$	=	The Partial derivative of side force Y on variable aileron deflection angle δa, m/s^2
$y_{\delta r}$	=	The Partial derivative of side force Y to rudder deflection angle variable δr, m/s^2
l_v	=	The Partial derivative of rolling moment L with to side force variable v, 1/ms
l_P	=	Partial derivative of rolling moment L with to rolling rate variable p, 1/s
l_r	=	Partial derivative of rolling moment L with to rate variable yaw r, 1/s
l_ϕ	=	The Partial derivative of rolling moment L with to roll angle variable ϕ, -
$l_{\delta a}$	=	The Partial derivative of rolling moment L with to aileron deflection angle variable δa, 1/s^2
$l_{\delta r}$	=	The Partial derivative of rolling moment L with to rudder deflection angle variable δr, 1/s^2
n_v	=	The Partial derivative of yawing moment N with to side force v, 1/ m s
n_P	=	The Partial derivative of yawing moment N with to rolling rate p, 1/s

n_r = The Partial derivative of yawing moment N with to yawing rate r, 1/s

n_ϕ = The Partial derivative of yawing moment N with to roll angle ϕ, -

$n_{\delta a}$ = The Partial derivative of yawing moment N with to aileron deflection angle δa, 1/s^2

$n_{\delta r}$ = The Partial derivative of yawing moment N with to rudder deflection angle δr, 1/s^2

1. Introduction

Parameter identification (PI) is a process of estimating the dynamic characteristics of a system in the form of dynamic property parameters using input history data and known output data (Klein & Morelli, 2006; Remple & Tischler, 2006). One method widely used in parameter identification is equation-error in the time domain. The equation-error method is based on linear regression using the ordinary least-squares principle. For example, the unknown aerodynamic parameter is estimated by minimizing the sum of the squared differences between the modelled aerodynamic forces and moments. Linear regression is a linear estimation problem, meaning that the model output depends linearly on the model parameters.

In the lateral-directional dimension, there are two inputs, aileron deflection and rudder deflection. The aileron is the control surface of the aircraft that controls the roll motion. The ailerons are located on the wings and move along the longitudinal axis. The type of stability that the aileron does is stabilize the aircraft in the lateral direction. While Rudder is the surface of control at the moment, the plane does yaw. Located on the vertical stabilizer and moves on the vertical (directional) axis. The type of stability carried out by the Rudder is to stabilize the aircraft in a directional direction.

For this research, we use data flight of C-5 A aircraft, a state-space matrix. The reason for choosing the data is because the data has been proven to be truly obtained from the real condition of the C-5 A aircraft during flight tests. C-5 A is a huge military logistics transport aircraft. The longitudinal control consists of four elevator sections with stabilizers, all moving for trim, roll control employing ailerons and spoilers, and conventional yaw steering control. The C-5 A uses stability augmentation on all axes. The C-5 has a high T-tail, a 25-degree wing sweep, and four TF39 turbofan engines (C-5A and B) mounted on pylons under the wings. These engines each had 43,000 pounds of thrust and 7,900 pounds (3,555 kilograms) of thrust each (Force, 2011).

This research uses the equation error method with the ordinary least square estimation technique to analyze parameter identification results based on the variation of aileron and rudder deflection input given. The research focuses on the lateral-directional dimension with the input deflection in the aileron and rudder control plane varied in 9 input cases. This research succeeded in obtaining the most suitable input combination for this dimension with flight test data for the C-5 A aircraft as an example.

2. Methodology

The stages of the research, same as the previous research (Jayanti et al., 2019), consist of conducting linear simulations, recording aircraft behavior, and identifying the results of the matrix against the reference. The modeling process is carried out using the aircraft input data and the existing flight test recording data.

2.1. Related Works

In the previous parameter identification research, LAPAN and POLBAN teams had identified parameters by observing the effect of control input using the corsair A-7A aircraft data in the longitudinal dimension (Jayanti et al., 2019). Jayanti's research used the equation error method with the ordinary least square estimation technique. The results show that the 3-2-1 input form has a smaller error value (RMSE) matrix A than the doublet and pulse input. The longer of simulation time, the error value (RMSE) for each input form is decreased. The RMSE (Root mean square error) value was calculated using matrix A between 0.38 - 0.46 (Jayanti et al., 2019). In the longitudinal dimension, based on the research that has been done, the 3-2-1 shape is the most suitable.

Several other researchers also carried out research related to parameter identification such as E. Plaetschke, Mulder, and Breeman. This study discusses the flight test results of five input signals for the identification of aircraft parameters (Plaetschke et al., 1983). Aircraft parameters are calculated using two different parameter identification algorithms, the classical maximum likelihood method, and flight path reconstruction followed by linear regression analysis. The aircraft used was the De Havilland DHC-2 Beaver experimental aircraft. The five signals are divided into three groups, namely high-frequency signals such as 3-2-1-1 and doublets, medium frequency signals, namely Mehra and DUT, and low-frequency signals, namely Schulz (Dr.P et al., 1979). The result of the comparison obtained is that, in general, the high-frequency signals seem to be somewhat superior to others. In particular, the control derivatives can be better estimated. Mehra signal is better in the symmetric case compared to the asymmetric case. Schulz's signal was inferior in almost every respect. The type of input signal has a considerable effect on the accuracy of parameter estimation (Plaetschke et al., 1983). Plaetschke's research was not focused on selecting the input form for the lateral dimension, but instead explained the comparison of the parameter estimation results obtained from data analysis for the five inputs with the method and the aircraft used.

The other research is research from NASA for the case Twin Otter flight test. The input is in lateral dimension with a pulse shape on the Rudder and a doublet shape on the aileron (Klein & Morelli, 2006). Another standard input is the 3-2-1-1 form. This input is sometimes challenging to use because three pulses are long and tend to push the aircraft out of flight conditions like the frequency sweep. Therefore, input 2-1-1 is used instead to overcome this problem (Klein & Morelli, 2006). The doublet input signal is bang-bang type, switching between plus and minus. This type of input is still widely used for the excitation of the characteristic longitudinal and lateral motion planes. Doublet and 3-2-1-1 have relatively high estimation accuracy results in controlling for aileron and rudder deflection derivatives in the lateral case. In the longitudinal case, 3-2-1-1 yields higher estimation accuracy in controlling for elevator deflection derivatives than DUT signals(Dr.P et al., 1979; Mulder et al., 1990).

Other research by E.A Morelli and V. Klein are about the optimal input design for estimating airplane parameters, using Dynamic Programming Principles (Morelli, 1990). Dynamic programming principles are used for designs in the time domain. This study used the Cramer-Rao lower bounds method. Morelli and Klein's research describes the optimal input design but does not focus on selecting of input forms, especially on the lateral-directional dimension.

Subsequent research by G. Licitra, A. Burger also discusses optimal input design for autonomous aircraft (Licitra et al., 2018). The optimal maneuver is obtained by solving the model problem with the time domain based on the optimum experimental design. OED (Optimal Experimental Design) and flight tests have been carried out for autonomous aircraft in the time domain. Compared to the widely used signal, the optimal solution is 3-2-1-1, and the Cramer-Rao Lower Bound assesses the estimated performance. In Licitra's research, an optimal input design has been generated with the calculated data, and it has been compared with the 3-2-1-1 input form. Still, in this study, for safety reasons, the optimal aileron sequence is not fully implemented.

Another study by Liliane Denis-Vidal et al. about estimating aircraft parameters with successive steps (Denis-Vidal et al., 2001). The optimal input is obtained by two different methods, namely dynamic programming principles and gradient algorithms. Analytical work for the same problem shows the square wave type input is better than the sinusoidal when the information is for parameter estimation (Chen, 1975). This study is for the longitudinal dimension only, and the authors explain that the least-squares criterion can be used to identify aircraft parameters. In Liliane's research, an optimal input design has been produced with the data from the estimation results, but the study is still only in the longitudinal dimension.

2.2. Problem Definition

This study will continue Jayanti's previous research, where previous research was only on the longitudinal dimension using the equation error method with the ordinary least square estimation technique. Therefore, this study aims to identify the most suitable input for IP in the lateral-directional dimension using the same process and observe the effect of simulation time. The input forms given are pulse, doublet, and 3-2-1-1. The simulation time can be divided into 25, 50, 100, 150, and 200 seconds. The input form is chosen based on the input form that is generally used based on previous studies and reference. At the same time, the selected time is only a trial for a range of 25 to 200 seconds. The input can adjust to get a suitable identification of all parameters (Gupta & Hall, 1975).

2.3. Method

Parameter identification (PI) aims to obtain the values of all the parameters in the model. Thus, to get figures from aircraft motion parameters (such as stability and control derivatives, Phugoid motion frequency, and damping), the parametric technique is used. The method that will be used is equation error. Chose this method because it is the most practical.
The state-space equation for motion dynamics:

$$\underline{\dot{x}} = A\underline{x} + B\underline{u} \tag{2-1}$$

This motion is recorded in a set of discrete-time intervals t. So the equation can be rewritten in the following form:

$$\underline{z} = H\underline{\theta} + \underline{v} \tag{2-2}$$

Where is $\underline{\theta}$ The vector of the searched parameter (which is not yet known) Then the parameter vector estimation is calculated using the OLS (Ordinary Least Square) error criteria, namely:

$$\underline{\theta} = [H'H]^{-1} + H'\underline{z} \tag{2-3}$$

3. Result and Analysis

Parameter identification in lateral/directional motion aims to obtain the following state-space values, with more than one input (multi-input), namely aileron and rudder deflection. The flight test data that will be used as material for testing the IP mechanism (parameter identification) is a virtual flight test for the C-5A aircraft at an altitude of 20,000 feet and a speed of Mach number 0.6 (Force, 2011), which is carried out by simulating the known linear equations.

Parameter identification in Multi Input Multi Output lateral motion aims to obtain the following state-space values:

$$\begin{Bmatrix} \dot{v} \\ \dot{p} \\ \dot{r} \\ \dot{\phi} \end{Bmatrix} = \begin{bmatrix} y_v & y_p & y_r & y_f \\ l_v & l_p & l_r & l_f \\ n_v & n_p & n_r & n_f \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{Bmatrix} v \\ p \\ r \\ \phi \end{Bmatrix} + \begin{Bmatrix} y_{\delta_a} & y_{\delta_r} \\ l_{\delta_a} & l_{\delta_r} \\ n_{\delta_a} & n_{\delta_r} \\ 0 & 0 \end{Bmatrix} \begin{vmatrix} \delta_a \\ \delta_r \end{vmatrix} \tag{3-1}$$

By plugging the values in the table into the above equation, we get:

$$\begin{Bmatrix} \dot{v} \\ \dot{p} \\ \dot{r} \\ \dot{\phi} \end{Bmatrix} = \begin{bmatrix} -0.10601 & 0 & -189.586 & 9.8073 \\ -0.0070 & -0.9880 & 0.2820 & 0 \\ 0.0023 & -0.0921 & -0.2030 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{Bmatrix} v \\ p \\ r \\ \phi \end{Bmatrix} + \begin{Bmatrix} -0.0178 & 3.3936 \\ 0.4340 & 0.1870 \\ 0.0343 & -0.5220 \\ 0 & 0 \end{Bmatrix} \begin{vmatrix} \delta_a \\ \delta_r \end{vmatrix} \tag{3-2}$$

In eq. (3-1), it can be seen that the number of state variables is m = 4 (i.e., v, p, r, and ϕ) and the number of inputs is 2, namely δ_a and δ_r.

If the motion of the plane stated in the state-space above is recorded in a set of discrete-time $t = t(0), t(1), \cdots, t(n)$ intervals and if eq. (2-1) holds, then at each point in time the equation- the equation also holds:

$$
\begin{array}{llllllll}
\dot{v}(0) & = y_v v(0) & +y_p p(0) & +y_r r(0) & +y_\phi \phi(0) & +y_{\delta_a}\delta_a(0) & +y_{\delta_r}\delta_r(0) & +\varepsilon(0) \\
\dot{p}(0) & = l_v v(0) & +l_p p(0) & +l_r r(0) & +l_\phi \phi(0) & +l_{\delta_a}\delta_a(0) & +l_{\delta_r}\delta_r(0) & +\varepsilon(0) \\
\dot{r}(0) & = n_v v(0) & +n_p p(0) & +n_r r(0) & +n_\phi \phi(0) & +n_{\delta_a}\delta_a(0) & +n_{\delta_r}\delta_r(0) & +\varepsilon(0) \\
\dot{\phi}(0) & = 0 & +0 & +r(0) & +0 & +0 & +0 & +\varepsilon(0) \\
\hline
\dot{v}(1) & = y_v v(1) & +y_p p(1) & +y_r r(1) & +y_\phi \phi(1) & +y_{\delta_a}\delta_a(1) & +y_{\delta_r}\delta_r(1) & +\varepsilon(1) \\
\dot{p}(1) & = l_v v(1) & +l_p p(1) & +l_r r(1) & +l_\phi \phi(1) & +l_{\delta_a}\delta_a(1) & +l_{\delta_r}\delta_r(1) & +\varepsilon(1) \\
\dot{r}(1) & = n_v v(1) & +n_p p(1) & +n_r r(1) & +n_\phi \phi(1) & +n_{\delta_a}\delta_a(1) & +n_{\delta_r}\delta_r(1) & +\varepsilon(1) \\
\dot{\phi}(1) & = 0 & +0 & +r(1) & +0 & +0 & +0 & +\varepsilon(1) \\
\hline
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \\
\hline
\dot{v}(n) & = y_v v(n) & +y_p p(n) & +y_r r(n) & +y_\phi \phi(n) & +y_{\delta_a}\delta_a(n) & +y_{\delta_r}\delta_r(n) & +\varepsilon(n) \\
\dot{p}(n) & = l_v v(n) & +l_p p(n) & +l_r r(n) & +l_\phi \phi(n) & +l_{\delta_a}\delta_a(n) & +l_{\delta_r}\delta_r(n) & +\varepsilon(n) \\
\dot{r}(n) & = n_v v(n) & +n_p p(n) & +n_r r(n) & +n_\phi \phi(n) & +n_{\delta_a}\delta_a(n) & +n_{\delta_r}\delta_r(n) & +\varepsilon(n) \\
\dot{\phi}(n) & = 0 & +0 & +r(n) & +0 & +0 & +0 & +\varepsilon(n)
\end{array}
\tag{3-3}
$$

Where $v(0), p(0), r(0),$ and $\phi(0)$are state variables measured at time $t = t(0)$, while $\delta_a(0)$ and $\delta_r(0)$ are deflections elevator is measured at time $t = t(0)$, and $\varepsilon(0)$ is the measurement error at time $t = t(0)$. Eq. (3-3) can be rewritten as follows:

$$
\begin{Bmatrix}
\dot{v}(0) \\ \dot{p}(0) \\ \dot{r}(0) \\ \dot{\phi}(0) \\ \hline \dot{v}(1) \\ \dot{p}(1) \\ \dot{r}(1) \\ \dot{\phi}(1) \\ \hline \vdots \\ \hline \dot{v}(n) \\ \dot{p}(n) \\ \dot{r}(n) \\ \dot{\phi}(n)
\end{Bmatrix}
=
\begin{bmatrix}
s(0) & 0_{1\times6} & 0_{1\times6} & 0_{1\times6} \\
0_{1\times6} & s(0) & 0_{1\times6} & 0_{1\times6} \\
0_{1\times6} & 0_{1\times6} & s(0) & 0_{1\times6} \\
0_{1\times6} & 0_{1\times6} & 0_{1\times6} & s(0) \\ \hline
s(1) & 0_{1\times6} & 0_{1\times6} & 0_{1\times6} \\
0_{1\times6} & s(1) & 0_{1\times6} & 0_{1\times6} \\
0_{1\times6} & 0_{1\times6} & s(1) & 0_{1\times6} \\
0_{1\times6} & 0_{1\times6} & 0_{1\times6} & s(1) \\ \hline
 & \vdots & & \\ \hline
s(n) & 0_{1\times6} & 0_{1\times6} & 0_{1\times6} \\
0_{1\times6} & s(n) & 0_{1\times6} & 0_{1\times6} \\
0_{1\times6} & 0_{1\times6} & s(n) & 0_{1\times6} \\
0_{1\times6} & 0_{1\times6} & 0_{1\times6} & s(n)
\end{bmatrix}
\begin{Bmatrix}
y_v \\ y_p \\ y_r \\ y_\phi \\ y_{\delta_a} \\ y_{\delta_r} \\ \hline l_v \\ l_p \\ l_r \\ l_\phi \\ l_{\delta_a} \\ l_{\delta_r} \\ \hline n_v \\ n_p \\ n_r \\ n_\phi \\ n_{\delta_a} \\ n_{\delta_r} \\ \hline 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0
\end{Bmatrix}
+
\begin{Bmatrix}
\varepsilon(0) \\ \varepsilon(0) \\ \varepsilon(0) \\ \varepsilon(0) \\ \hline \varepsilon(1) \\ \varepsilon(1) \\ \varepsilon(1) \\ \varepsilon(1) \\ \hline \vdots \\ \hline \varepsilon(n) \\ \varepsilon(n) \\ \varepsilon(n) \\ \varepsilon(n)
\end{Bmatrix}
\tag{3-4}
$$

In Eq. (3-4), $s(n) = \{v(n) \quad p(n) \quad r(n) \quad \phi(n) \quad \delta_a(n) \quad \delta_r(n)\}$ a row matrix of size $1 \times l$ with $l = m + u = 4 + 2 = 6$, while $0_{1\times6} = \{0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0\}$. This equation can be rewritten in the general form, namely:

$$\underline{z} = H\underline{\theta} + \underline{v} \tag{3-5}$$

Where $\underline{z}$ is a matrix or vector of recorded state parameter values, at discrete time intervals: H is a state matrix, as presented in equation (8), which has dimensions $n \times (ml) = n \times (4 \cdot 6) = n \times 24$, namely:

$$H = \begin{bmatrix} s(0) & 0_{1\times6} & 0_{1\times6} & 0_{1\times6} \\ 0_{1\times6} & s(0) & 0_{1\times6} & 0_{1\times6} \\ 0_{1\times6} & 0_{1\times6} & s(0) & 0_{1\times6} \\ 0_{1\times6} & 0_{1\times6} & 0_{1\times6} & s(0) \\ \hline s(1) & 0_{1\times6} & 0_{1\times6} & 0_{1\times6} \\ 0_{1\times6} & s(1) & 0_{1\times6} & 0_{1\times6} \\ 0_{1\times6} & 0_{1\times6} & s(1) & 0_{1\times6} \\ 0_{1\times6} & 0_{1\times6} & 0_{1\times6} & s(1) \\ \hline & \vdots & & \\ \hline s(n) & 0_{1\times6} & 0_{1\times6} & 0_{1\times6} \\ 0_{1\times6} & s(n) & 0_{1\times6} & 0_{1\times6} \\ 0_{1\times6} & 0_{1\times6} & s(n) & 0_{1\times6} \\ 0_{1\times6} & 0_{1\times6} & 0_{1\times6} & s(n) \end{bmatrix} \tag{3-6}$$

While $\underline{\theta}$ is the parameter vector to be searched for, namely:

$$\underline{\theta} = \left\{ \begin{array}{c} y_v \\ y_p \\ y_r \\ y_\phi \\ y_{\delta_a} \\ y_{\delta_r} \\ \hline l_v \\ l_p \\ l_r \\ l_\phi \\ l_{\delta_a} \\ l_{\delta_r} \\ \hline n_v \\ n_p \\ n_r \\ n_\phi \\ n_{\delta_a} \\ n_{\delta_r} \\ \hline 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{array} \right\} \tag{3-7}$$

The parameter vector sought is $\underline{\theta}$ (which is not yet known), calculated using the OLS (Ordinary Least Square) error criterion, such as eq. (2-3).

Aileron and rudder deflection is varied in three forms, namely pulse, doublet, and 3-2-1-1. In addition to different input variations, the maximum time will also be distinguished, namely 25, 50, 100, 150, and 200 seconds. The pulse input form has a duration of 1 second by 1 degree. The doublet input form has a duration of 1 second of 1 degree, and then 1 second of -1 degree, and so on is zero. The input form 3-2-1-1 has a duration of 3

seconds of 1 degree, then 2 seconds of -1 degree, then 1 second of 1 degree, and another 1 second of 1 degree, so on is zero.
In this study, 9 test scenarios will be carried out, namely as follows: Aileron will be given input first and then Rudder with a difference of 1 second.

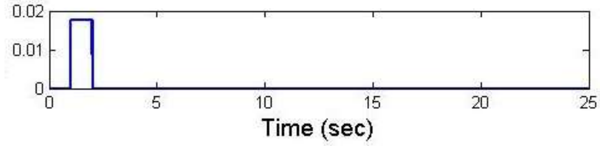

Figure 3-2: Pulse Input

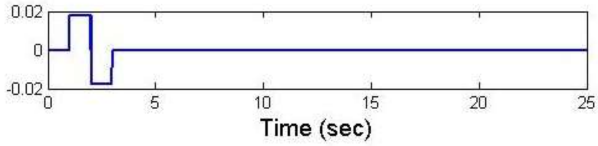

Figure 3-1: Double Input

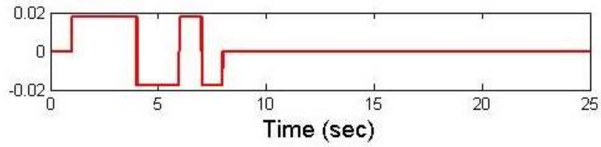

Figure 3-3: 3211 Input

Table 3-1: Test Case

	Input Form	
	Aileron	Rudder
1	Pulse	Pulse
2	Doublet	Doublet
3	3-2-1-1	3-2-1-1
4	Pulse	Doublet
5	Pulse	3-2-1-1
6	Doublet	Pulse
7	Doublet	3-2-1-1
8	3-2-1-1	Pulse
9	3-2-1-1	Doublet

The IP calculation as an example is in the form of a doublet input for ailerons and rudders with a maximum time of 25 seconds, and the results are as follows:

$$A_{real} = \begin{bmatrix} y_v & y_p & y_r & y_f \\ l_v & l_p & l_r & l_f \\ n_v & n_p & n_r & n_f \\ 0 & 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} -0.10601 & 0 & -189.586 & 9.8073 \\ -0.0070 & -0.9880 & 0.2820 & 0 \\ 0.0023 & -0.0921 & -0.2030 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$A_{PI} = \begin{bmatrix} y_v & y_p & y_r & y_f \\ l_v & l_p & l_r & l_f \\ n_v & n_p & n_r & n_f \\ 0 & 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} -0.10489 & -0.3176 & -190.098 & 9.818 \\ -0.00687 & -0.95904 & 0.2932 & -0.00226 \\ 0.002503 & -0.0562 & -0.1584 & -0.00147 \\ -1.5803 & 1 & 2.3616 & 2.5728 \end{bmatrix}$$

$$B_{real} = \begin{Bmatrix} y_{\delta_a} & y_{\delta_r} \\ l_{\delta_a} & l_{\delta_r} \\ n_{\delta_a} & n_{\delta_r} \\ 0 & 0 \end{Bmatrix} = \begin{Bmatrix} -0.0178 & 3.3936 \\ 0.4340 & 0.1870 \\ 0.0343 & -0.5220 \\ 0 & 0 \end{Bmatrix}$$

$$B_{PI} = \begin{Bmatrix} y_{\delta_a} y_{\delta_r} \\ l_{\delta_a} \; l_{\delta_r} \\ n_{\delta_a} n_{\delta_r} \\ 0 \quad 0 \end{Bmatrix} = \begin{Bmatrix} 0.0451 & 2.845 \\ 0.4264 & 0.1855 \\ 0.0280 & -0.5126 \\ -1.294 & -1.355 \end{Bmatrix}$$

Furthermore, with matrix A and, B the results of the identification of these parameters, namely A_{PI} and B_{PI}Simulations can be carried out on the same aileron and rudder input responses, and the results are as follows:

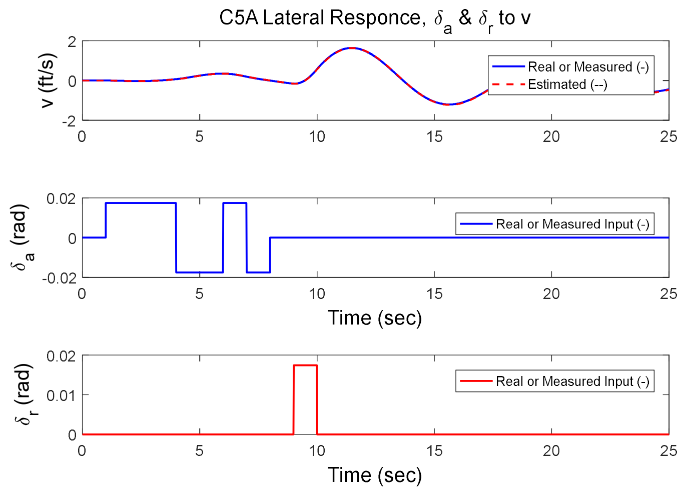

Figure 3-4: The lateral input response to v in the original and estimated data

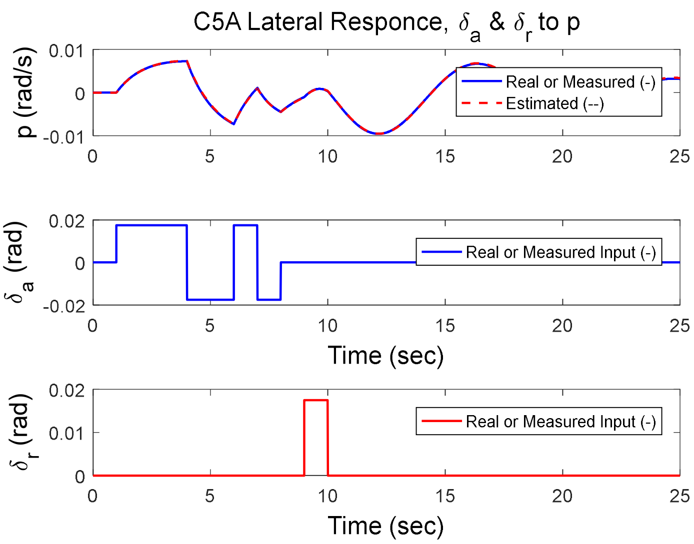

Figure 3-5: The lateral input response for p in the original and estimated data

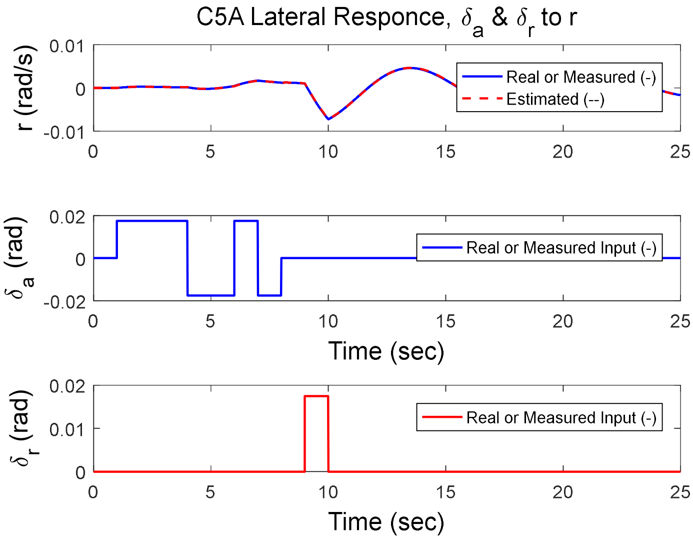

Figure 3-6: The lateral input response to r in the original and estimated data

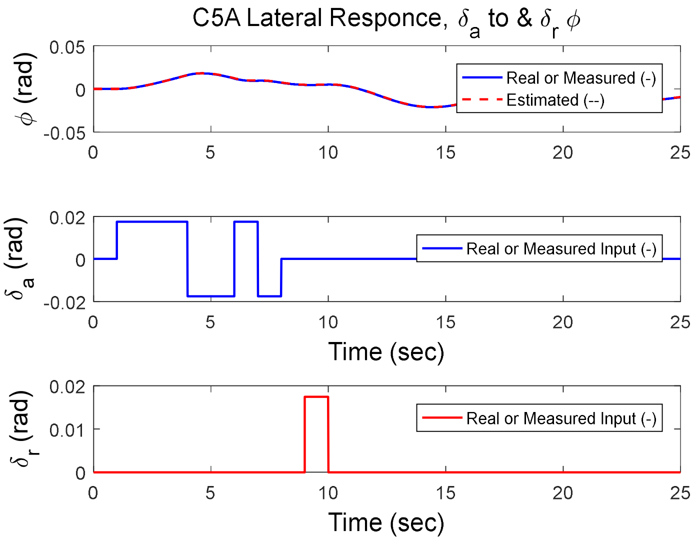

Figure 3-7: The lateral input response to ϕ in the original and estimated data

Furthermore, the RMSE (Root mean square error) value will be observed in the results of the identification of matrix A parameters for all cases, with the following formula:

$$RMSE = \sqrt{\frac{1}{m \times n} \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} [f(i,j) - g(i,j)]^2} \quad (3\text{-}8)$$

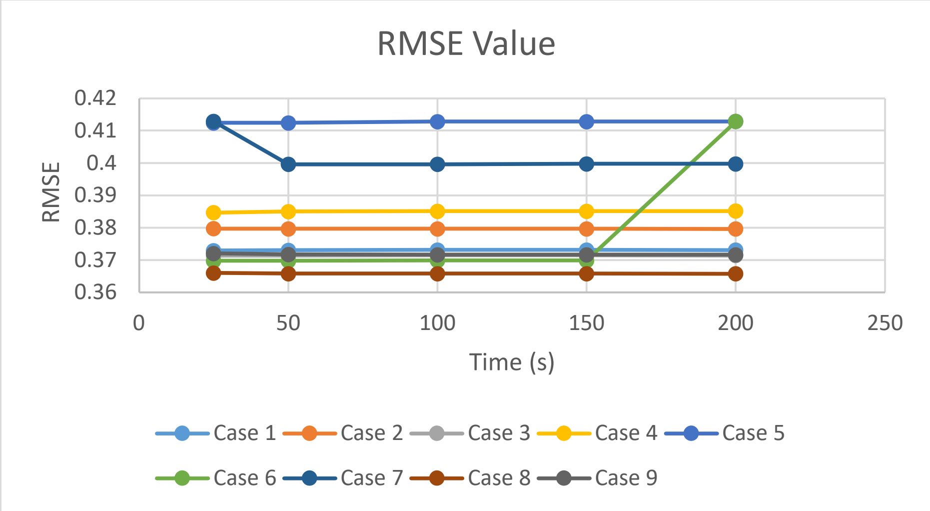

Figure 3-8: Comparison of RMSE Value in each Test Case in Graphic

Table 3-2: Comparison of RMSE Value in each Test Case in Table

case	25 s	50 s	100 s	150 s	200 s
1	0.372974	0.373063941	0.37310116	0.373109	0.373111
2	0.379721	0.379642297	0.37963934	0.379639	0.379639
3	0.371384	0.371385044	0.37142583	0.371436	0.371439
4	0.384697	0.385002849	0.38512834	0.385155	0.385162
5	0.412423	0.412423312	0.41283379	0.412867	0.412876
6	0.369818	0.369818309	0.36983126	0.369831	0.412876
7	0.412876	0.399640347	0.39964035	0.399779	0.399787
8	0.366029	0.365790968	0.36577454	0.365772	0.365771
9	0.372095	0.371707334	0.37169973	0.371699	0.371699

(Figure 3-8) and (Table 3-2) shows that case 8 has the lowest RMSE value or error among other cases. Case 8 is a 3-2-1-1 aileron input and a pulse rudder input. At the same time, the highest error value is case 5, with aileron pulse input and rudder input in the form of 3-2-1-1. The result is slightly different from V. Klein and E. A Morelli, who in their book, explains that the input form in lateral dimension is implemented in the pulse form on the Rudder and the doublet form on the aileron (Klein & Morelli, 2006). However, according to the state of input that is acceptable and can be utilized by the flight test communication (Mulder et al., 1990) and results of research (Plaetschke et al., 1983), the signal 3-2-1-1 is one of them is superior to the other. In this lateral dimension simulation, the simulation time in each case does not always make the error value decrease. In cases, namely cases, 1,3,4,5, and 6, the error value increases in proportion to the longer simulation time. While in cases 2, 7, 8, and 9, the RMSE value decreases as the simulation time gets longer.

Table 3-3: Comparison with other research

	Research			
	This Research	V Klein and Morelli	Mulder	Plaetschke
Recommended Input	3-2-1-1 Aileron input	Doublet Aileron Input	3-2-1-1	3-2-1-1
	Pulse Rudder input	Pulse Rudder Input		

4. Conclusions

The results of parameters identification in the lateral-directional dimension using C-5 A aircraft data indicate that aileron input in the form of 3-2-1-1 and the rudder input in the form of the pulse has the lowest error value among all cases. The method used is equation error with ordinary least square. Therefore, the combination of control input with 3-2-1-1 aileron input and pulse rudder input is most suitable for the lateral-directional dimension among all cases. The longer simulation time does not always indicate a decreasing error value (RMSE) in each input form. In some cases, the RMSE value increases with increasing simulation time. The results are same with Mulder and Plaetschke research that 3-2-1-1 is one of them is superior to the other and slightly different with input used in V-Klein and Morelli's books that use doublet in aileron and pulse in rudder input. The selection of information can excite the motion mode properly to know the dynamic characteristics of the aircraft more accurately. The dynamic characteristics of the aircraft will be related to stability analysis and aircraft control making. So this research is essential.

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