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Research Article

# Parameter Estimation of Short-period Low Order Equivalent System for Fighter Aircraft Under Extreme Flight Conditions

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## Abstract

This paper presents the estimation of Low Order Equivalent System (LOES) parameters for the longitudinal short-period mode of a fighter aircraft, using high-fidelity nonlinear simulation data of the F-16. The complex flight dynamics of such aircraft, effectively a High Order System (HOS) due to the presence of flight controls and component dynamics, require simplified equivalent systems for evaluating flying qualities against military standards. This study focuses on estimating LOES short period parameters using nonlinear flight simulation data under extreme flight conditions defined by high angles of attack up to 30 degrees. LOES parameters were identified through a hybrid approach combining time-domain regression and frequency-domain parameter estimation using a Maximum Likelihood Estimation (MLE) algorithm, resulting accurate identifications characterized by low standard deviations. Model validation confirms that LOES output closely matches HOS nonlinear data using inputs in the time domain, with a coefficient of determination $R^2$ metric above 77% and fit error below 0.2. Additionally, the LOES model effectively represents nonlinear system responses in the frequency domain, yielding relatively low MIL cost and maintaining mismatch errors within the Maximum Unnoticeable Added Dynamics (MUAD) boundary.

## Keywords

Equivalent System, Flight Dynamics, Flight Simulations, Parameter Estimation, System Identification

## 1. Introduction

High-maneuverability fighter aircraft represent complex high-order systems (HOS), primarily due to the integration of digital fly-by-wire (FBW) flight control systems. These systems, which include control laws, artificial feel systems, sensor dynamics, filters, and actuator dynamics, are essential for achieving optimal performance and precise control across a wide range of flight conditions, supported by real-time computations via robust flight control computers [1].

Historically, flying qualities criteria and military specifications, such as MIL-STD-1797A [2], were developed based on data from unaugmented aircraft exhibiting classical dynamic responses. In longitudinal dynamics, these responses are typically described by two principal modes: the phugoid (long-period) and the short-period mode. To bridge the gap between these classical models and the complex behavior of aug-

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mented aircraft, the concept of a Low Order Equivalent System (LOES) was introduced [2]. This allows for the application of established flying qualities metrics to modern, highly augmented aircraft designs.

Numerous flight test research programs [1, 3, 4] have demonstrated the effectiveness of LOES in correlating pilot-perceived flying and handling qualities with the dynamic responses of augmented aircraft, despite their inherent high-order and nonlinear characteristics. Beyond this, LOES modeling plays a key role in validating linear control law designs and serves as a simplified reference model for simulation and control synthesis within defined flight envelopes [1]. Recent studies have further demonstrated LOES applications in rapid flying qualities evaluation [5] and robust control law design under handling quality constraints [6]. LOES has also been used to define desired dynamics and evaluate control systems for supersonic trainers [7] and during gun-firing transients [8], reinforcing its value as a practical engineering tool in high-demand flight control environments.

However, the operational envelope of modern fighter aircraft is continually pushed towards extreme flight conditions, particularly at high angles of attack, where strong aerodynamic nonlinearities emerge. Several studies have investigated aerodynamic parameter estimation in these regimes. For example, Kumar and Ghosh [9] modeled nonlinear longitudinal aerodynamics of the Hansa-3 aircraft near stall, while others focused on the HARV [10] with angle of attack (AoA) up to 50°, and the X-31 [11] up to 70°. More recently, advanced techniques such as neural networks have been employed for aerodynamic parameter estimations at high AoA [12, 13].

While these studies have advanced aerodynamic parameter estimation at high AoA, they have not specifically focused on identifying LOES parameters for the short-period mode. This simplification is crucial for evaluating flying/handling qualities and validating control law designs under military standards, particularly in high-AoA conditions where nonlinear effects dominate.

This study focuses on identifying LOES parameters for the longitudinal short-period mode of a fighter aircraft operating under extreme flight conditions characterized by high AoA, using nonlinear flight simulation data. To address the complexities of this regime, a hybrid identification framework is implemented, extending traditional time-domain regression and frequency-domain Maximum Likelihood Estimation. This methodology incorporates the Golden Section Search and Simplex algorithms to refine the frequency-domain parameter estimation, ensuring robust convergence despite the high degree of aerodynamic nonlinearity. The resulting LOES models are validated through time-domain analysis by quantifying response discrepancies, and through frequency-domain analysis by comparing mismatches against Maximum Unnoticeable Added Dynamics (MUAD) tolerance envelopes. This integrated approach is essential for assessing flying/handling qualities and evaluating control law designs under extreme conditions.

## 2. Setup and Methodology

The estimation of short period LOES parameters is based on nonlinear flight data, which can be obtained from either actual flight tests or high-fidelity simulation tests. The estimation process involves multiple stages, starting with data transformation and frequency response analysis, followed by parameter estimation using optimization techniques. The overall methodology for LOES parameter estimation is outlined in the following workflow diagram shown in Figure 1.

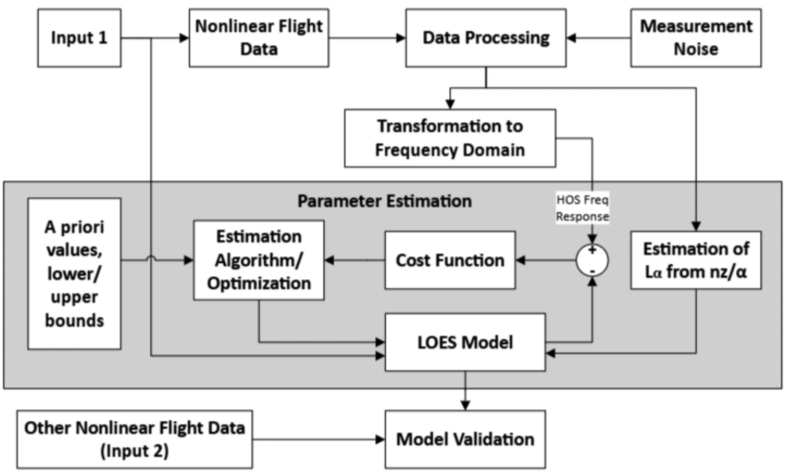


***Figure 1.*** *Overall process for LOES estimation.*

### 2.1. Data Transformation Method

Selected input-output (I/O) which is elevator command ($\delta_{e\,cmd}$) and pitch rate ($q$) respectively is first detrended to remove any bias & linear trends. The noisy part of pitch rate is also reduced using low-pass filter. The data is then segmented using a Hanning window with 80% overlap as suggested by Tischler and Remple [14] to smooth out edges and minimize distortions. After that, the Power Spectral Density (PSD) and Cross-Spectral Density (CSD) are computed to characterize the spectral properties. The PSD describes the power distribution of the input and output signals over frequency, while the CSD captures their frequency-domain relationship. These estimates are then smoothed using the Welch method, which divides the data into overlapping segments, applies the Fast Fourier Transform (FFT) to each segment, and averages the results. From the smoothed spectral estimates, the system's frequency response is derived by taking the ratio of the CSD to the input PSD. Additionally, the coherence function is calculated to assess the linearity of the input-output relationship. A coherence value close to 1 indicates a strong linear relationship, whereas lower values suggest the presence of noise or nonlinear effects. A coherence value above 0.6 in a stable frequency region is considered a reliable indicator of a well-estimated frequency response [14]. The initial frequency range of interest for LOES short period estimation is from 0.5–10 rad/s.

## 2.2. LOES Parameter Estimation Algorithm

For the short period mode, the closed-loop response of the pitch rate ($q$) to the elevator deflection command ($\delta e_{cmd}$) is modeled in the form of a transfer function as [2]:

$$\frac{q(s)}{\delta_{ecmd}(s)} = \frac{K_q(s+L_\alpha)\ e^{-\tau\ s}}{s^2+2\ \zeta_{sp}\omega_{nsp}\ s+\ \omega_{nsp}^2} \tag{1}$$

where $K_q$ is the equivalent gain for the pitch rate, $L_\alpha$ is the gradient (slope) of the lift curve, $\tau$ is the equivalent time delay (in seconds), $\zeta_{sp}$ is the equivalent short period damping ratio, and $\omega_{n_{sp}}$ is the equivalent short period natural frequency (in rad/s).

To estimate these five LOES parameters ($L_\alpha, K_q, \zeta_{sp}, \omega_{n_{sp}}, \tau$), this study proposes a hybrid identification approach, combining time-domain and frequency-domain methods to enhance robustness under high-AoA flight conditions. First, the $L_\alpha$ parameter is estimated separately using a time-domain relationship involving $n_z/\alpha$, which is the ratio of normal acceleration to the angle of attack. As formulated in Equation (2), $L_\alpha$ is computed from:

$$L_\alpha = \frac{n_z}{\alpha} \times \frac{g}{V_{TAS}} \tag{2}$$

This relationship is adapted from the method used in F-16XL flight test research by Stachowiak and Bosworth [4] where $L_\alpha$ was determined from flight test data prior to full system identification. In this study, the $n_z/\alpha$ value is obtained from the average slope of the $n_z$ versus α graph in the low-frequency region of the data, while the $V_{TAS}$ speed is taken from the trim condition at the beginning of the input. The remaining four parameters, denoted $\hat{\theta} = \left[K_q, \zeta_{sp}, \omega_{n_{sp}}, \tau\right]$ are estimated using a frequency-domain Maximum Likelihood Estimation (MLE) method applied to the nonlinear simulation data representing the high-order system (HOS). This hybrid approach is motivated by the different sensitivities and estimation strengths of each domain: the static gain $L_\alpha$ is more accurately captured in the time domain using direct signal ratios, particularly at high-AoA where traditional frequency-based gain estimation may become less reliable. In contrast, dynamic parameters such as damping ratio, natural frequency, and time delay are better extracted in the frequency domain, where spectral methods naturally suppress noise and highlight the dominant system dynamics [14, 16].

In the frequency-domain MLE framework, the residual between the measured and modeled frequency responses is used to estimate an output noise covariance matrix $R$, which is incorporated into the cost function. The objective is to minimize the determinant of $R$, as expressed in Equation (4), thereby reducing the variance of the frequency-domain residuals and improving estimation robustness. Parameter optimization is performed using the Gauss-Newton iterative algorithm, with initial values set based on prior knowledge and constrained by upper and lower bounds to ensure stability and realistic estimates as provided in Table 1.

$$R = \frac{1}{N}\sum_{k=1}^{N}[z_k - y_k][z_k - y_k]^T \tag{3}$$

$$J(\theta) = \det(R) \tag{4}$$

***Table 1.*** *Upper/lower bounds for LOES parameter.*

| Parameter | Lower Bound | Upper Bound |
|---|---|---|
| $K_q$ | -1000 | 1000 |
| $\zeta_{sp}$ | 0.01 | 3.00 |
| $\omega_{n_{sp}}$ | 0.1 | 30 |
| $\tau$ | 0 | 1 |

To improve convergence, the Golden Section Search method is used to refine initial parameter values before applying the Gauss-Newton algorithm, which struggles with poor convergence when starting values are far from optimal. The iteration process is stopped when one of the following convergence criteria is achieved [15]:

$$\left|\left(\hat{\theta}_j\right)_k - \left(\hat{\theta}_j\right)_{k-1}\right| < 1.0 \times 10^{-5} \quad \forall j, j = 1,2,\dots,n_p \tag{5}$$

$$\left|\left(\frac{\partial J(\theta)}{\partial \theta_j}\right)_{\theta=\hat{\theta}_k}\right| < 5.0 \times 10^{-2} \quad \forall j, j = 1,2,\dots,n_p \tag{6}$$

$$\left| \frac{J(\hat{\theta}_k) - J(\hat{\theta}_{k-1})}{J(\hat{\theta}_{k-1})} \right| < 0.001 \quad (7)$$

If the Gauss-Newton algorithm fails to converge within the maximum iterations, the Nelder-Mead Simplex method is used as an alternative to optimize parameter values. The flowchart diagram below illustrates the estimation algorithm.

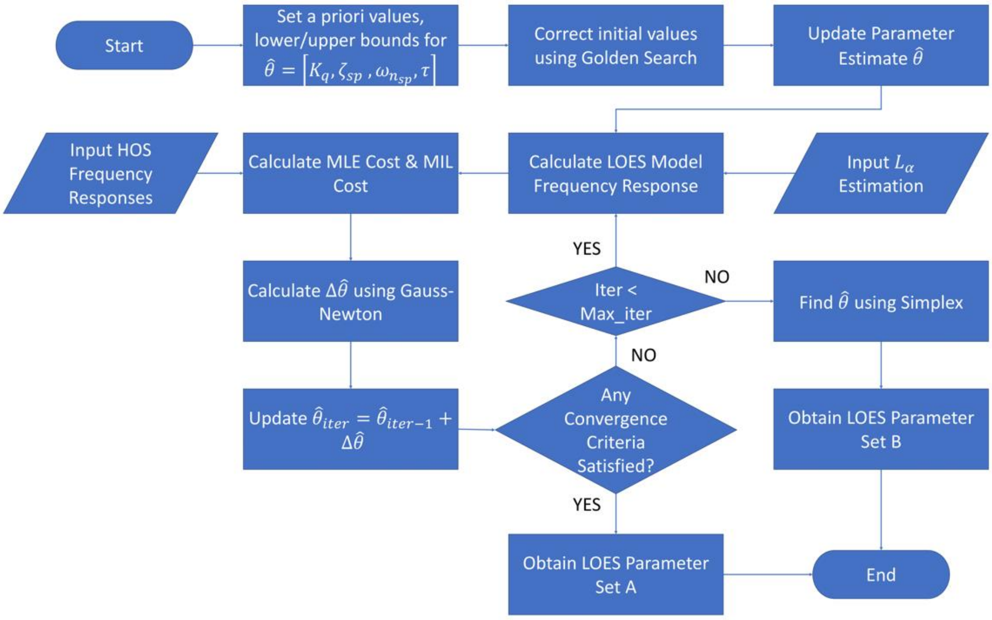


***Figure 2.*** *LOES parameter estimation algorithm.*

## 2.3. Model Validation Method

Model validation involves several methods, including statistical accuracy, residual analysis, and model's predictive capability. The statistical accuracy of the estimated parameters is quantified using the standard deviation ($\sigma_\theta$), which is derived from the Fisher information matrix during the frequency-domain estimation process. In the time domain, standard deviations are obtained through regression analysis. Residual analysis is conducted in both the time and frequency domains to assess how well the model captures system behavior. In the time domain, common metrics include the fit error (FE) and the coefficient of determination ($R^2$) [16]. The fit error in Equation (8), reflects the mean squared error across the data set, while $R^2$, defined in Equation (9) and (10), indicates the proportion of variance in the measured output that is explained by the model. A perfect fit model is characterized by an FE of 0 and an $R^2$ of 1.

$$FE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(z_i(t_k) - y_i(t_k)\right)^2} \quad i = 1,2,..n \quad (8)$$

$$R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T} \quad (9)$$

$$SS_T = \sum_{i=1}^{N}(z_i - \bar{z})^2, SS_E = \sum_{i=1}^{N}(z_i - \hat{y}_i)^2, SS_R = \sum_{i=1}^{N}(\hat{y}_i - \bar{z})^2 \quad (10)$$

In the frequency domain, model validation is performed using the LOES short period cost function, as defined in MIL-STD-1797A and expressed by the Equation (11) [2]. This military standard also introduces the concept of a boundary envelope known as Maximum Unnoticeable Added Dynamics (MUAD) as depicted in Figure 3 [18], within which gain and phase errors are assessed. If the model's error plots remain inside this envelope, the LOES model is considered sufficiently accurate in replicating the high-order system (HOS) response and is thus acceptable for flying qualities evaluation [17].

$$MIL\ \ cost = \frac{20}{n}\sum_{j=1}^{n}[(gain_{data} - gain_{LOES})^2 + 0.02(phase_{data} - phase_{LOES})^2] \quad (11)$$

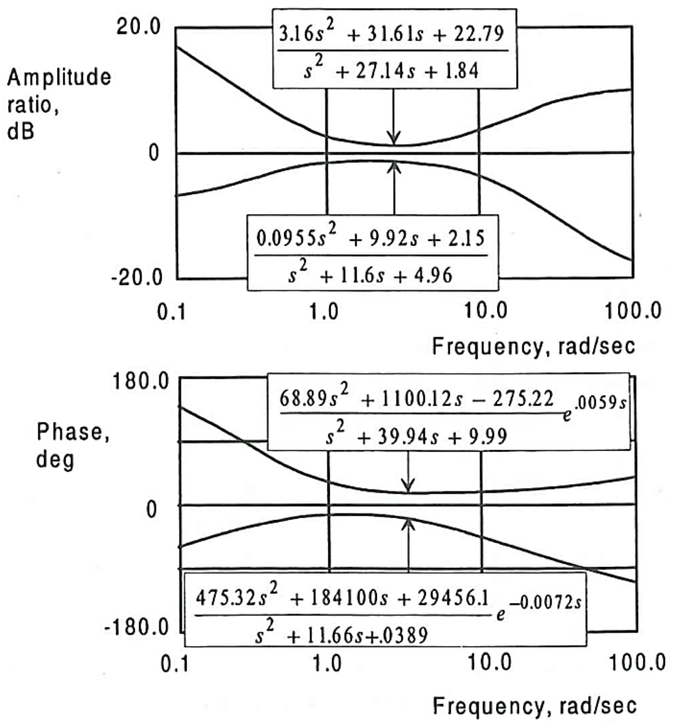


*Figure 3. MUAD envelope for LOES short period in terms of gain and phase boundaries.*

The final validation approach is the model's predictive capability or proof of match (POM). This method evaluates how well the identified model replicates the system's actual time-domain response when subjected to identical control inputs. The predictive performance is quantified using fit error (FE) and the coefficient of determination ($R^2$).

## 2.4. Flight Simulation Data

In this study, the nonlinear flight simulation data was obtained from F-16 MATLAB/Simulink model developed by Russell [19] with high-fidelity aerodynamics data [20] the simulation operates at a high sampling rate which is 120 Hz, replicating real flight data. The flight simulation is performed under two cases of extreme flight conditions characterized by high AoA ($\alpha$) as provided in Table 2.

*Table 2. Extreme flight condition cases.*

| Case | Altitude, h [ft] | Mach [-] | $V_{TAS}$ [knot] | AoA, [deg] |
|---|---|---|---|---|
| 1 | 20000 | 0.24 | 145 | 25.3 |
| 2 | 20000 | 0.21 | 131 | 30.0 |

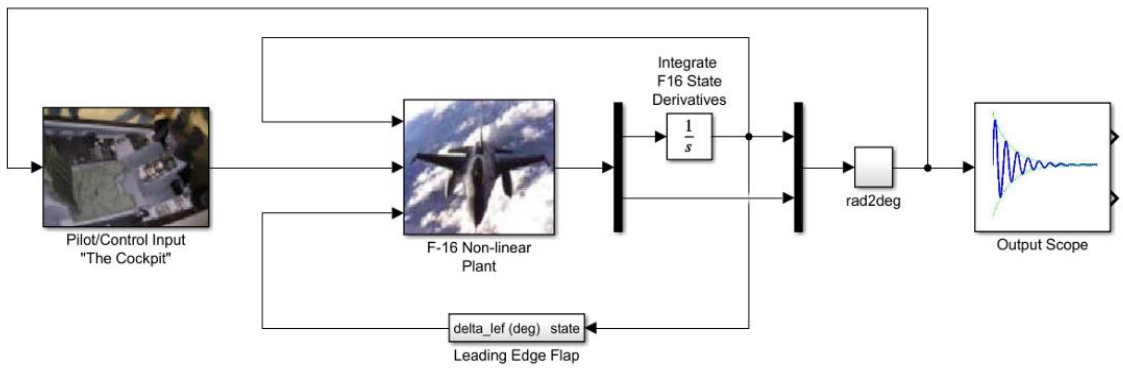


*Figure 4. F-16 Simulink nonlinear model.*

To excite the short period dynamics, a 3211 elevator command input ($\delta_{e_{cmd}}$) is applied. To emulate realistic flight measurement conditions, random Gaussian noise is added to the output signals: pitch rate ($q$), normal acceleration ($n_z$), and angle of attack ($\alpha$). The noise amplitude is tuned to ensure an acceptable signal-to-noise ratio (SNR) exceeding 10, as recommended by Morelli [15]. The nonlinear simulation data used in this study is illustrated in the figure below.

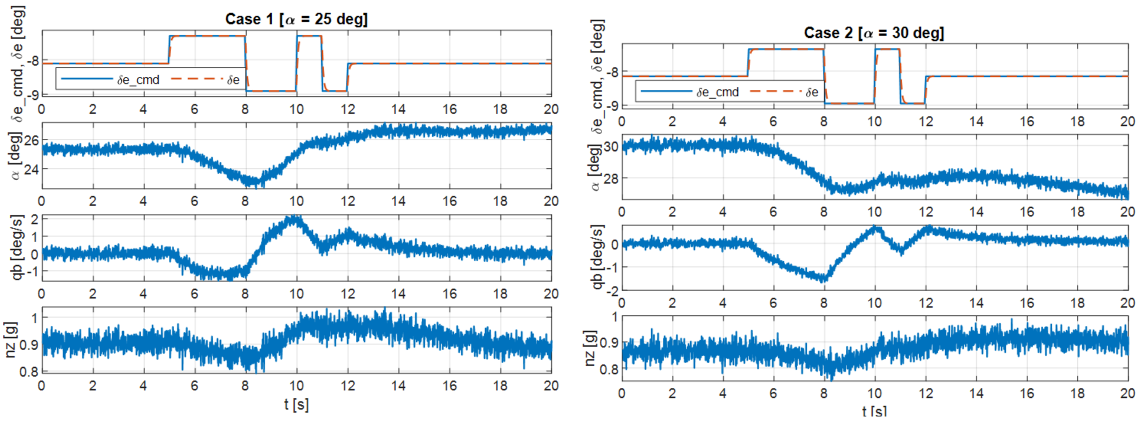


***Figure 5.*** *Nonlinear flight simulation data on both Case 1 & 2.*

## 3. Results and Discussion

This section presents the results and discussion of the LOES parameter estimation. The analysis begins with the frequency response and coherence function derived from filtered I/O flight data from both flight condition cases, as shown in the figure below. As observed in Figure 6, the coherence values are consistently above the accepted threshold of 0.6 within the frequency range of approximately 0.5 rad/s to 6 rad/s. This level of coherence suggests that, within this band, the simulation data exhibits a sufficiently linear relationship suitable for reliable frequency-domain system identification techniques. However, for frequencies exceeding approximately 6 rad/s (up to 10 rad/s), a noticeable degradation in coherence is evident for both cases. This decrease is attributed to the increased relative influence of the additive white noise at these higher frequencies. Based on this analysis, the frequency range of interest for the subsequent LOES parameter estimation was narrowed and defined between 0.5 rad/s and 6 rad/s.

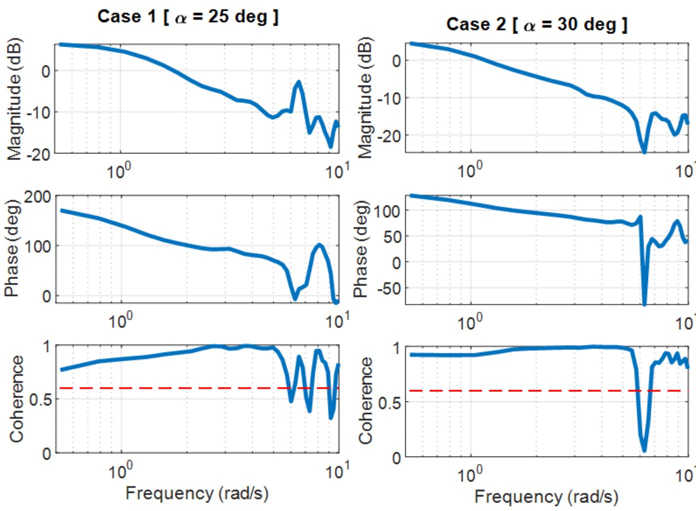


***Figure 6.*** *Frequency response of simulation data on both Case 1 & 2. Red dashed-line indicates the coherence threshold of 0.6.*

Subsequently, the estimation of $L_\alpha$ from time-domain data is carried out. The relevant data used ($n_z$ and $\alpha$) are passed through necessary filtering to reduce the effect of noise. After getting the slope of $n_z/\alpha$ through regression, the $L_\alpha$ is obtained using Equation (2). The standard deviation of $L_\alpha$ is calculated through error propagation from standard deviation of $n_z/\alpha$ slope using same equation. The results are summarized in the following table and figure. The $L_\alpha$ estimate demonstrates good predictive quality, evidenced by a low standard deviation.

***Table 3.*** *Result of $L_\alpha$ Estimation.*

| Case | $n_z/\alpha \pm \sigma$ [g/rad] | $L_\alpha \pm \sigma$ [1/s] |
|---|---|---|
| 1 | 1.4530 ± 0.0123 | 0.1911 ± 0.0016 |
| 2 | 1.3003 ± 0.0077 | 0.1885 ± 0.0011 |

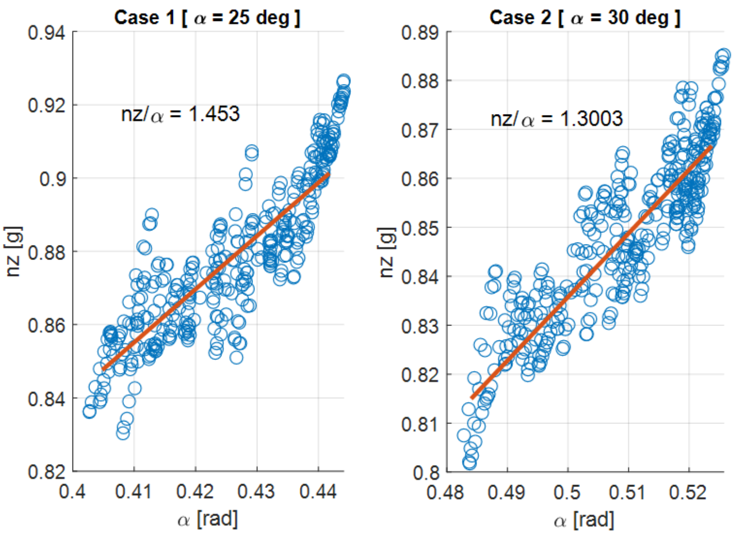


***Figure 7.*** *Slope of $n_z/\alpha$ from nonlinear simulation data.*

Using the previously determined $L_\alpha$, the remaining four LOES parameters: $K_q, \zeta_{sp}, \omega_{n_{sp}}, \tau$ were estimated by fitting to the HOS frequency response data. The results of this parameter estimation for both cases, including their respective standard deviations ($\sigma$), are summarized in Table 4. These parameters were then used to construct the LOES transfer function models, provided in Equation (12) and (13). The frequency response of the resulting LOES model is then compared to that of the nonlinear HOS data, as illustrated in Figure 8. The minimized MIL cost function values are approximately 25.02 for Case 1 and 6.82 for Case 2, both of which are considered relatively low.

***Table 4.*** *Result of $L_\alpha$ Estimation.*

| Parameters | Values + $\sigma$ | |
|---|---|---|
| | Case 1 | Case 2 |
| $L_\alpha$ | 0.1911 ±0.0016 | 0.1885 ±0.0011 |
| $K_q$ | -1.6005 ± 0.0384 | -1.2617 ± 0.0106 |
| $\zeta_{sp}$ | 0.6369 ±0.0452 | 1.1172 ±0.0703 |
| $\omega_{n_{sp}}$ | 0.67765 ±0.0259 | 0.32739 ±0.0170 |
| $\tau$ | 0.09415 ±0.0069 | 0.07197 ±0.0016 |

$$LOES_{case\ 1} = \frac{-1.601\ s - 0.3058}{s^2 + 0.8633\ s + 0.4592}\ e^{-0.0942\ s} \tag{12}$$

$$LOES_{case\ 2} = \frac{-1.262\ s - 0.2379}{s^2 + 0.7315\ s + 0.1072}\ e^{-0.072\ s} \tag{13}$$

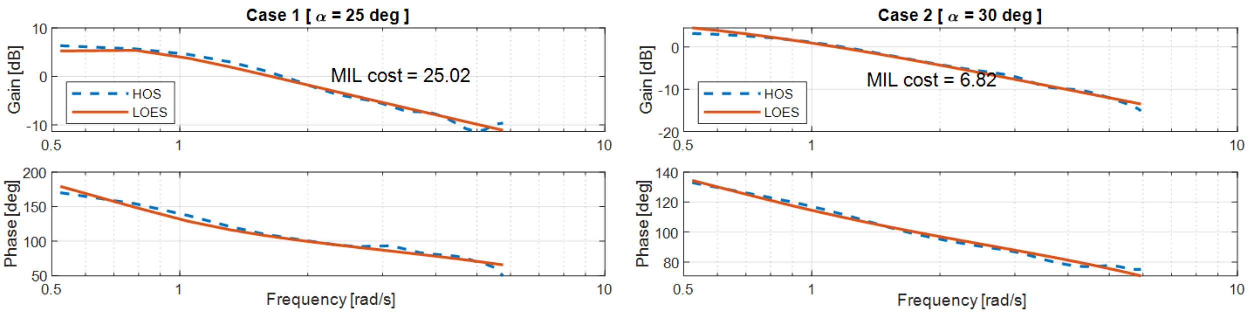


*Figure 8. Frequency response of HOS nonlinear data & LOES models.*

The gain & phase difference between HOS nonlinear data and identified LOES model are plotted within the MUAD boundary, as illustrated in the figure below. The results indicate that all mismatches remain inside the MUAD boundaries, confirming that the discrepancies fall within the tolerance range of added dynamics imperceptible to the pilot. This suggests that the LOES model is sufficiently accurate for evaluating flying qualities based on MIL-STD-1797A criteria.

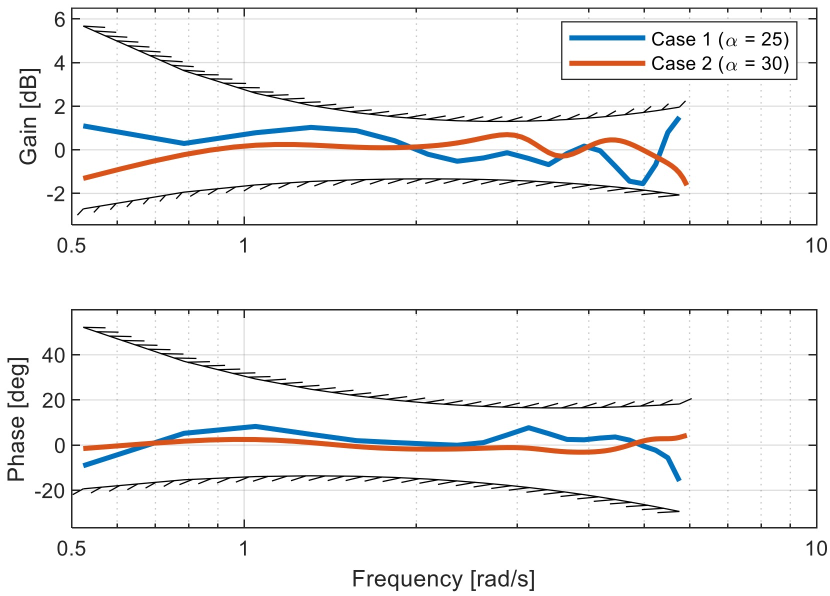


*Figure 9. LOES mismatch versus MUAD boundaries. The mismatch for both cases are inside the boundaries.*

Further validation method to evaluate the identified LOES model is model predictive capability or proof of match in time-domain. The model predictive capability of LOES was evaluated using representative elevator command inputs—3211 and doublet—applied to both the nonlinear simulation and the LOES model. By comparing the resulting pitch rate responses, two key metrics were computed: fit error (FE) and the coefficient of determination ($R^2$), which measure the closeness of the LOES model response to the nonlinear system.

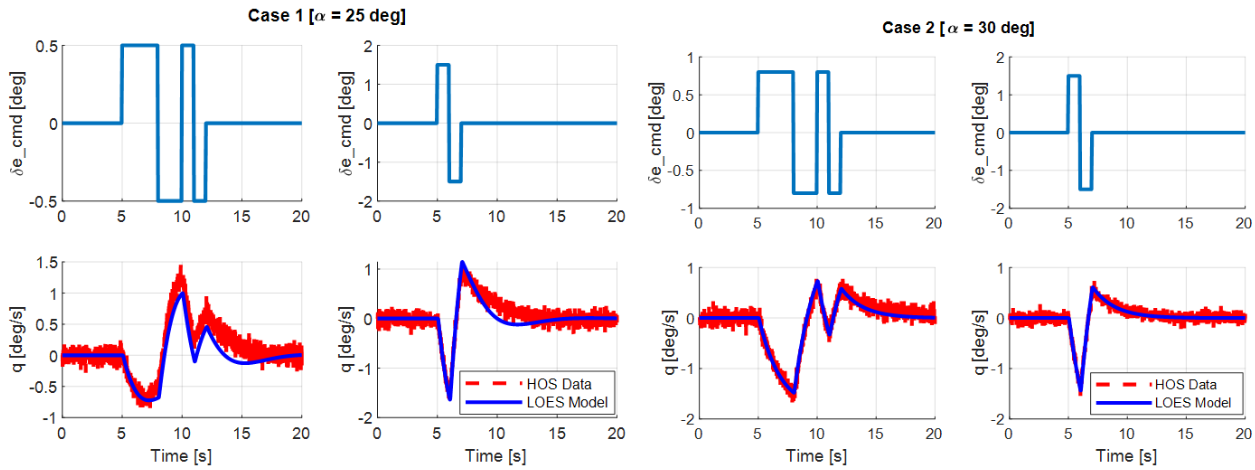


*Figure 10. Time response of nonlinear data & LOES models.*

*Table 5. LOES model residual analysis.*

| Input | FE | | $R^2$ | |
|---|---|---|---|---|
| | Case 1 | Case 2 | Case 1 | Case 2 |
| 3211 | 0.1972 | 0.1112 | 0.7754 | 0.9482 |
| Doublet | 0.1542 | 0.0760 | 0.8337 | 0.9265 |

The analysis showed that the LOES model was able to reasonably capture the pitch rate dynamics under both extreme flight conditions. For Case 1 with AoA 25 degrees, the LOES model achieved a fair to good match. For the 3211 input, the fit error (FE) was 0.1972 with a coefficient of determination ($R^2$) of 0.7754, while the doublet input showed improved agreement, with a lower FE of 0.1542 and a higher $R^2$ of 0.8337. These results indicate that the model effectively tracked the primary features of the nonlinear pitch rate response, particularly during initial command transitions. In Case 2 with AoA 30 degrees, the model performance improved further. For the 3211 input, the LOES yielded an FE of 0.1112 and $R^2$ of 0.9482, and for the doublet input, the FE is lower to 0.0760 with an $R^2$ of 0.9265. These metrics reflect a strong correlation between the LOES model and HOS simulation data, even under more nonlinear aerodynamic conditions. It should be noted that a direct numerical comparison with other high-AoA identification studies [9-13] is not feasible, as those works focus on full-scale aerodynamic coefficient extraction rather than LOES parameters. Furthermore, since those studies do not typically report standard fit metrics such as $R^2$ or Fit Error, the validation of the current approach relies on compliance with the MUAD envelopes defined in MIL-STD-1797A. This ensures the identified parameters meet the established industry standards for flying qualities evaluation, which is the primary objective of this research.

From these results, the LOES model demonstrated good predictive capability for the short-period mode dynamics across both extreme conditions, effectively tracking primary response trends. The discrepancies observed in the time-domain response are within acceptable bounds, particularly because the frequency-domain mismatches remain inside the MUAD envelopes defined by MIL-STD-1797A. This implies that the differences are unlikely to be perceptible to the pilot or to negatively impact flying and handling qualities, reinforcing the validity of the LOES approach for high-AoA control law assessment.

Despite these promising results, several limitations regarding the scope of this study must be addressed. While the use of high-fidelity nonlinear simulation data allowed for controlled validation, real-world flight test environments introduce unmodeled dynamics such as atmospheric turbulence, structural vibrations, and sensor biases that may influence identification robustness. Furthermore, the LOES framework relies on a quasi-linear approximation of the aircraft's short-period mode; while this proved effective for the 25°–30° AoA range investigated here, the model's predictive accuracy may degrade in deeper stall regimes or during high-amplitude maneuvers where axial coupling and strong aerodynamic nonlinearities become dominant. Finally, the assumption of ideal sensor and actuator dynamics neglects hardware-specific uncertainties like hydraulic pressure variations or rate limiting, which would require further consideration in physical aircraft implementations.

Beyond validation, the identified LOES models have direct practical utility in both control law tuning and flight testing workflows. In control system development, these LOES representations allow engineers to quickly assess and adjust short-period characteristics such as damping ratio and natural frequency to ensure compliance with handling qualities requirements defined in MIL-STD-1797A. For example, control designers can tune inner-loop pitch response to match the desired LOES dynamics derived from high-AoA conditions, ensuring consistent behavior across the envelope. Additionally, during flight testing, LOES models offer a simplified reference for evaluating pilot feedback by correlating perceived handling deficiencies with deviations in the model dynamics. At high AoA, where full nonlinear analysis is computationally intensive and time-consuming, the LOES provides an efficient tool for identifying handling boundaries, assessing augmentation system performance, and serving as a reduced-order plant model for future control synthesis and envelope protection design.

## 4. Conclusions

This study successfully estimated and validated Low Order Equivalent System (LOES) parameters for the short-period mode of a fighter aircraft under high-angle-of-attack conditions using nonlinear simulation data. The hybrid methodology—combining time-domain regression with frequency-domain Maximum Likelihood Estimation refined by Gauss-Newton and Simplex algorithms—yielded accurate parameters with low standard deviations. Validation results confirmed high model fidelity, with frequency-domain mismatches remaining within the MUAD tolerance envelopes and time-domain predictive accuracy exceeding $R^2$ of 0.77 for Case 1 and $R^2$ of 0.92 for Case 2. These metrics, alongside low MIL cost values, demonstrate that the LOES models effectively capture the dominant aircraft dynamics for flying qualities evaluation.

While the feasibility of the approach is demonstrated, the study's scope is limited by its reliance on linear LOES structures and simulation data, which may not fully account for the unmodeled dynamics and hardware-specific uncertainties encountered in actual flight environments. Consequently, future work should prioritize validation using real flight test data to assess model robustness under operational disturbances. Additionally, exploring data-driven identification methods, such as neural networks, could offer enhanced adaptability across highly nonlinear regimes and broader flight envelopes.

## Abbreviations

| | |
|---|---|
| HOS | High-Order Systems |
| FBW | Fly-by-Wire |
| MIL | Military |
| STD | Standard |
| LOES | Low Order Equivalent System |
| AoA | Angle of Attack |
| I/O | Input-Output |
| PSD | Power Spectral Density |
| CSD | Cross-Spectral Density |
| FFT | Fourier Transform |
| MLE | Maximum Likelihood Estimation |
| FE | Fit Error |
| MUAD | Maximum Unnoticeable Added Dynamics |
| POM | Proof of Match |
| SNR | Signal-to-Noise Ratio |

## Author Contributions

**Sayogyo Rahman Doko:** Conceptualization, Data curation, Formal Analysis, Methodology, Resources, Software, Visualization, Writing – original draft, Writing – review & editing

**Rianto Adhy Sasongko:** Supervision, Validation

## Data Availability Statement

The data that support the findings of this study can be found at: https://github.com/will214/F16FlightControl

## Conflicts of Interest

The authors declare no conflicts of interest.

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# Biography

**Sayogyo Rahman Doko**, M.Sc. is an aerospace engineer at PT Dirgantara Indonesia (Indonesian Aerospace), specializing in flight control law and flight dynamics and control. He earned his Bachelor's degree in Aerospace Engineering from Institut Teknologi Bandung (ITB) in 2016 and his Master's degree from the same institution in 2025. He currently serves as a Flight Control Law Engineer and Flight Dynamics & Control Engineer, and is the Project Leader of Flight Physics for the Unmanned Aircraft System (UAS) program. His work covers control law design, flight control development, flying and handling qualities, and stability analysis. He has participated in various domestic and international aerospace projects, including the N219 engineering flight simulator, H225M full flight simulator, KF-21/IFX fighter aircraft development, and the PUNA MALE unmanned aerial vehicle program.

**Rianto Adhy Sasongko**, Ph.D. is an Associate Professor at the Faculty of Mechanical and Aerospace Engineering, Institut Teknologi Bandung (ITB), Indonesia. He earned his Bachelor's degree in Aerospace Engineering from ITB in 1997, a Master's degree in Automatic Control and Systems Engineering from the University of Sheffield in 2000, and a Ph.D. in Electrical and Electronic Engineering from Imperial College London in 2008. He delivers courses in system dynamics, flight dynamics, and flight control to both Aerospace and Mechanical Engineering students. His research focuses on dynamical systems and control, with emphasis on aerospace applications, including flutter suppression, robust control, and convex optimization. Since 2020, he has been serving as the Chair of the Undergraduate Study Program in Aerospace Engineering at ITB. In addition to teaching and research, he is also active in professional communities and collaborative academic activities.

# Research Field

**Sayogyo Rahman Doko:** Flight dynamics & control, flight control law design & analysis, aircraft parameter estimation, aircraft handling qualities, flight control development.

**Rianto Adhy Sasongko:** Control systems for aerospace applications, system dynamics and modeling, robust control design, flutter suppression techniques, convex optimization in control.