SSY230 - Project3 - System Identification of F-16 Aircraft Using Multisine Excitation Data

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June 6, 2024

Abstract

This report presents the system identification of an F-16 aircraft using multisine excitation data. The goal is to identify a model that accurately describes the system dynamics, focusing on the acceleration measured at the excitation point. The process includes data preparation, model estimation, validation, and analysis of the chosen model.

Introduction

The aim of this project is to perform system identification on data recorded under multisine excitations with a full frequency grid. The data consists of acceleration measurements at the excitation point, with inputs being the force and voltage signals. We focus on estimation data at level 3 (36.8 N RMS) and validation data at level 2 (24.6 N RMS).

Data Preparation

We prepared the data by loading the estimation and validation datasets, creating `iddata` objects in MATLAB, and visualizing the data. No pre-processing was needed as the data was already well-prepared for system identification.

Visualization

Initial visualization of the data was crucial for inspecting the signals and ensuring their suitability for model identification. Figure 1 shows the time plot of estimation (blue) and validation data (green). The signals appear clean and consistent, indicating that the data is well-prepared and ready for model estimation. This conclusion is drawn from the visual inspection of the time plot, which shows no significant anomalies or irregularities.

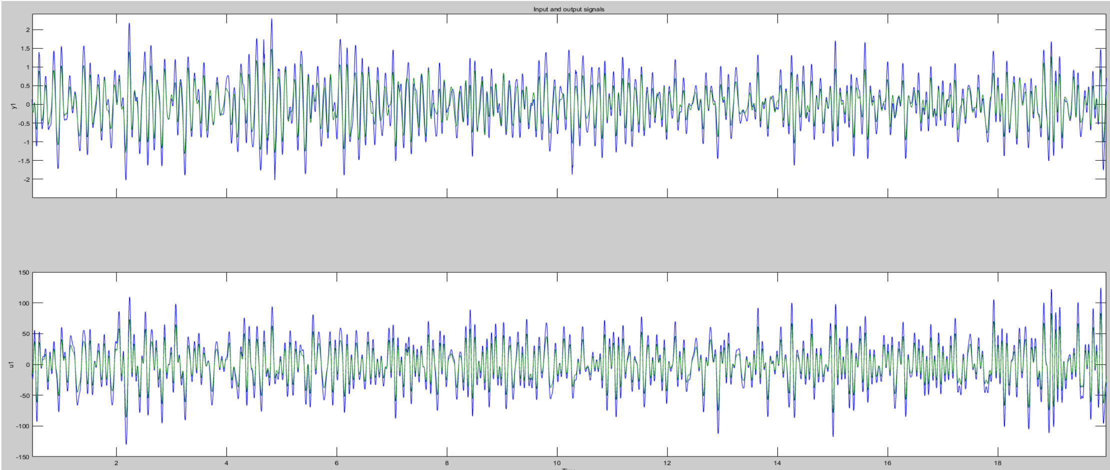

Figure 1: Time plot of estimation and validation data. The signals are clean and consistent, suitable for model estimation.

Additionally, a zoomed-in view of the y1 time plot is provided in Figure 2 to clearly show the signal details and highlight the data characteristics.

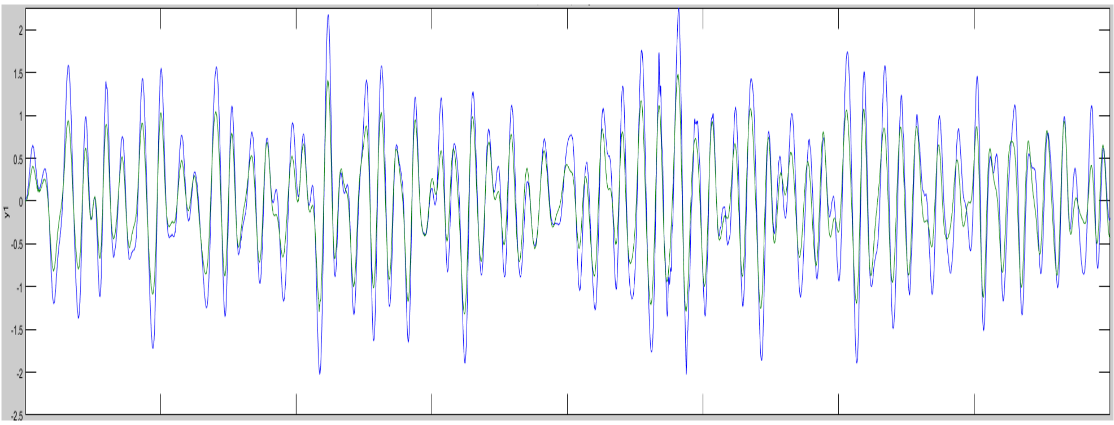

Figure 2: Zoomed-in view of the time plot of estimation and validation data, highlighting the clean and consistent signal characteristics.

Model Estimation and Validation using Simulated Output

We used the System Identification Toolbox GUI in MATLAB to estimate various models, including ARX, ARMAX, OE, Box-Jenkins, State-Space, and Transfer-Function models. The selection of the best model was based on the fit percentage as an initial indication of which model is better to start with. The best model obtained was an OE model with a fit percentage of 88.34%. Figures 3, 4, and 5 provide comparisons of the best model-fits.

Model Validation

The OE441 model estimated using the prediction error method was validated by plotting the model output against the true validation dataset, showing a good match between the actual and modeled outputs according to the best-determined fit percentage. **The data here have been estimated using simulation**. In this context, simulation refers to the process where the model's output is generated using the input signal and the model parameters without any correction from the actual observed outputs during the simulation. Figures 3, 4, and 5 show the model validation results for the OE, ARX, and BJ models, respectively.

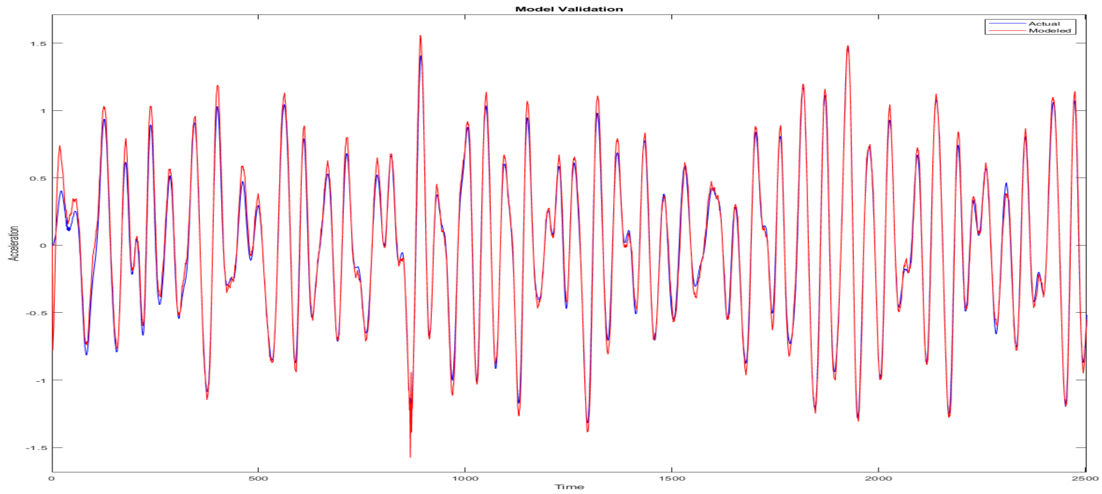

Figure 3: Model validation: Actual vs. Modeled output (OE441 WITH FIT = 88.34%).

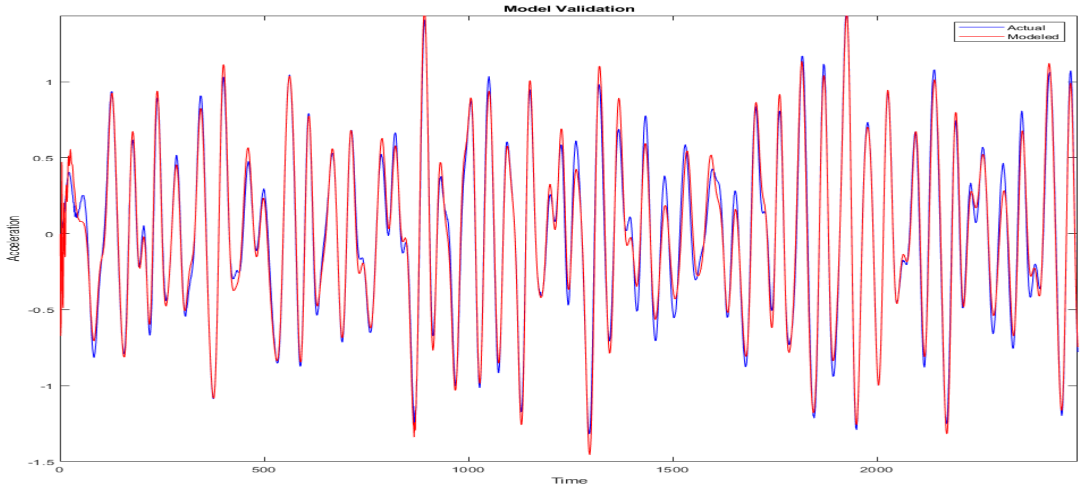

Figure 4: Model validation: Actual vs. Modeled output (ARX771 WITH FIT = 81.31%).

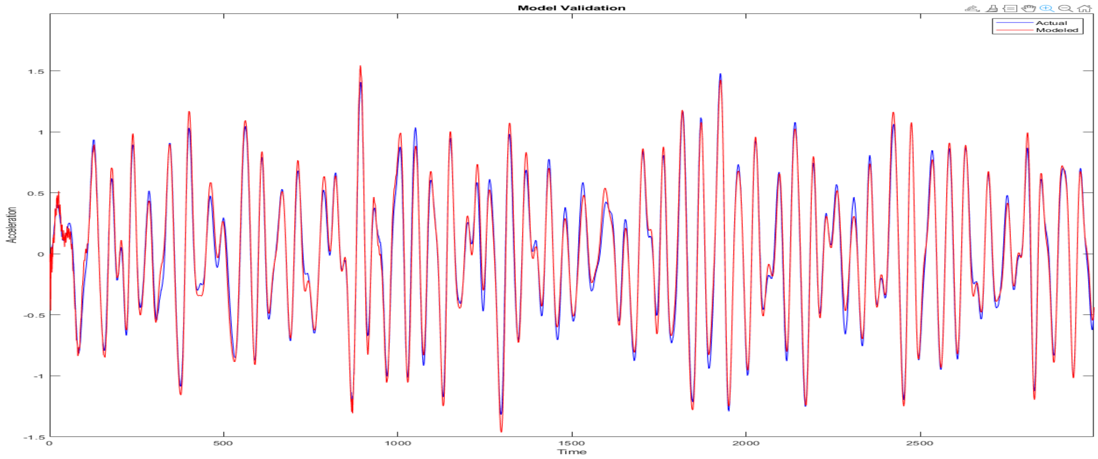

Figure 5: Model validation: Actual vs. Modeled output (BJ66661 WITH FIT = 83.16%).

Model Estimation and Validation using One-Step-Ahead Prediction

We also utilized the System Identification Toolbox GUI in MATLAB to estimate models using the one-step-ahead prediction method. This method estimates the next output value based on current and past input and output data, and is particularly useful for validating the immediate predictive accuracy of the model. Initially, the selection of the optimal model was based on the fit percentage, but further validation using additional metrics ensured robustness and accuracy. The best model obtained using one-step-ahead prediction is an ARX model with a model order of 6, defined as follows:

- **na (number of poles) = 6:** This represents the number of past output terms used in the model.
- **nb (number of zeros) = 6:** This indicates the number of past input terms used in the model.
- **nk (input delay) = 1:** This specifies the delay between the input and output signals.

This ARX model (denoted as ARX661) achieved a fit percentage of 98.3196%, showing a highly accurate model.

Model Validation

The ARX661 model, validated using the one-step-ahead prediction method, yielded a fit percentage of 98.3196%. One-step-ahead prediction allows the model to use actual past outputs to predict the next output, providing a step-by-step correction mechanism that resulted in higher predictive accuracy. The validation against the validation dataset confirmed a good match between the actual and modeled outputs, as shown in the following Figure 6 where the true (blue) output is plotted against the modeled (red) output:

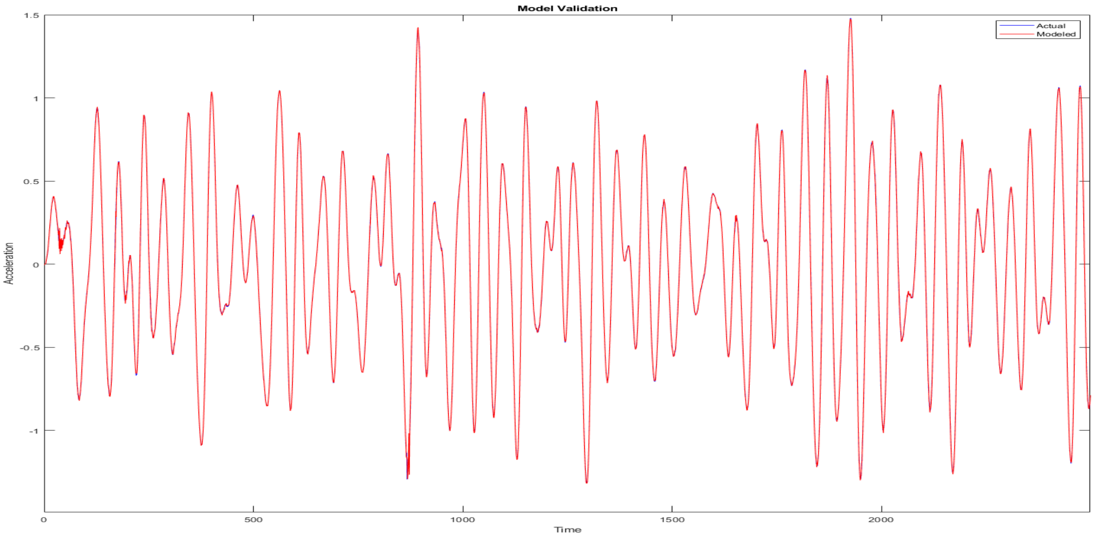

Figure 6: Model validation: Actual vs. Modeled output (ARX661 WITH FIT = 98.3196%).

Prediction Error Analysis

To evaluate the accuracy of the ARX661 model, we calculated the Normalized Root Mean Square Error (NRMSE) based on the one-step-ahead prediction. The NRMSE provides a measure of the prediction error relative to the standard deviation of the actual output data.

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{t=1}^{N}(y(t) - \hat{y}(t))^2}}{\text{std}(y)} \tag{1}$$

The NRMSE for the ARX661 model was found to be 0.016804, indicating minimal prediction error and high model accuracy.

Residual Analysis

Residual analysis was performed to ensure the adequacy of the ARX661 model. The residuals, which are the differences between the actual output and the model output, were analyzed to verify that they are white noise (uncorrelated and zero mean). analyzing the residuals is essential because ARX models are designed to minimize the prediction error by explicitly modeling the relationship between inputs and outputs. Unlike OE models, which primarily focus on the system output, ARX models take into account the error dynamics. Therefore, ensuring that the residuals are white noise confirms that the ARX model has effectively captured all the significant dynamics driven by the inputs. If the residuals were not white noise, it would suggest that there are unmodeled dynamics that the ARX model failed to capture.

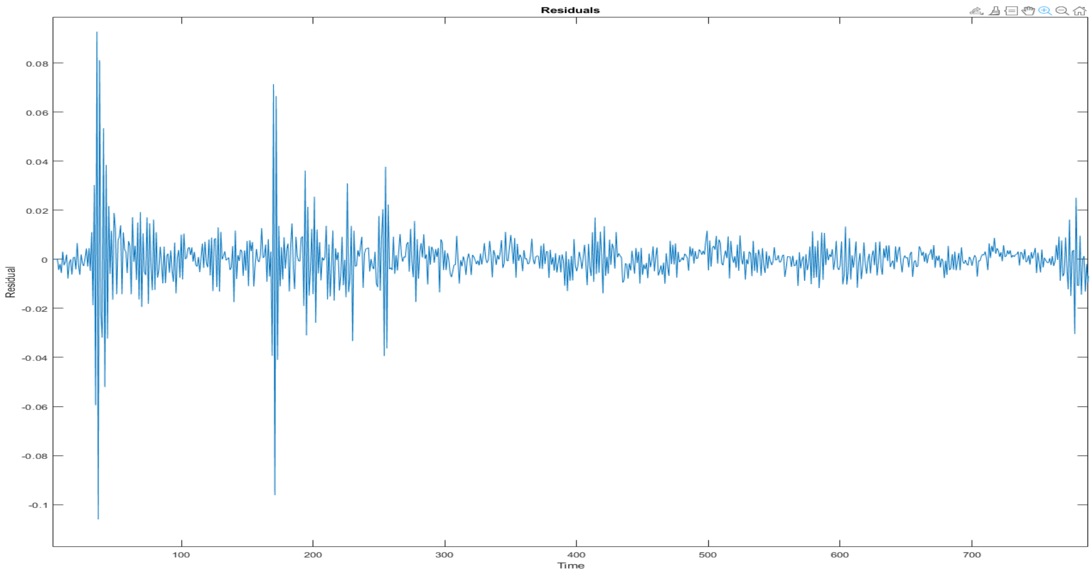

Figure 7: Residuals of the ARX661 model.

Insight from the Residuals Plot

The residuals plot (Figure 7) shows that the residuals oscillate around zero with no apparent patterns or trends. This indicates that the model has captured the majority of the system dynamics, and the remaining errors are minimal and mostly random noise.

Stability Analysis

To assess the stability and behavior of the ARX661 model, we analyzed the poles and zeros of the system along with their 95% confidence intervals. The poles and zeros plot (Figure 8) provides insights into the system's stability and the confidence in our estimates.

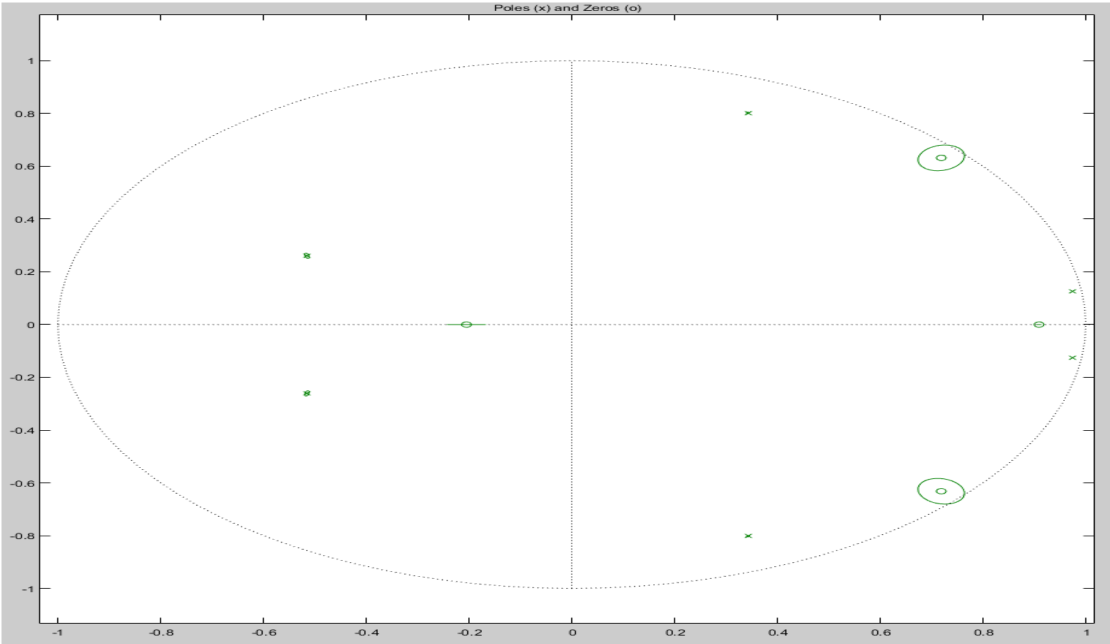

Figure 8: Pole-zero map of the ARX661 model, showing all poles within the unit circle ($x \rightarrow poles \longleftrightarrow o \rightarrow zeros$)

Observations from the Poles and Zeros Plot

The poles and zeros of the ARX661 model are shown in the complex plane. All poles are within the unit circle, confirming that the system is stable. The confidence intervals around the poles and zeros provide an indication of the reliability of these estimates.

Conclusion

In this project, we successfully identified and validated a highly accurate model for the F-16 aircraft dynamics using the ARX661 model. The model demonstrated excellent fit and prediction accuracy, stability, and robustness across various validation metrics.

References

J.P. Noël and M. Schoukens, F-16 aircraft benchmark based on ground vibration test data, 4TU.ResearchData, Dataset, doi: 10.4121/12954911.