ONLINE IDENTIFICATION OF POWER GRID MODELS VIA SYNCHROPHASOR DATA

An Undergraduate Research Scholars Thesis

by

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TABLE OF CONTENTS

Page

ABSTRACT

Online Identification of Power Grid Models Via Synchrophasor Data

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Power system dynamics are becoming increasingly complex, as new interconnections are made between systems and more power from renewable resources is integrated into the electric grid. As a result, assessing and maintaining the stability of power systems is becoming more and more challenging. There is a need for better, simpler dynamical models to allow system operators and others to make quick, smart decisions about system operation. Fortunately, the widespread adoption of Phasor Measurement Units (PMUs) has allowed more data to be collected regarding power system operation. This research investigates how to leverage PMU data to produce accurate dynamical models through Bode analysis. Assuming system input is perfectly known and controllable, it is shown that Bode phase and magnitude plots can be constructed empirically by inputting a sum of sine waves into a linear system and observing the output. However, problems arise when this technique is applied to a noisy system, and the resulting Bode plots are shown to be unreliable. Since introducing large sinusoidal oscillations into a power system is undesirable, it is concluded that producing dynamical models through Bode analysis is impractical in real power systems. Instead, future work will investigate model identification methods more resilient to system noise, including recursive parallel, equation error, and output error methods. Once effective modeling methods are identified for linear systems, methods for

modeling non-linear systems will be considered. Also, applications of MATLAB's System Identification Toolbox in deriving these models will be examined.

ACKNOWLEDGMENTS

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NOMENCLATURE

dB	Decibel
DFT	Discrete Fourier Transform
ERCOT	The Electric Reliability Council of Texas
FERC	Federal Energy Regulatory Commission
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
GPS	Global Positioning System
IEEE	Institute of Electrical and Electronics Engineers
IIR	Infinite Impulse Response
ISO	Independent System Operator
NASPI	North American SynchroPhasor Initiative
NERC	North American Electric Reliability Corporation
PES	Power and Energy Society
PMU	Phasor Measurement Unit, or Synchrophasor
SMA	Selective Modal Analysis
SNR	Signal-to-Noise Ratio

CHAPTER I

INTRODUCTION

Power systems across North America are becoming more complex, in response to rising demand, increasing grid interconnections, and growing incorporation of renewable resources. Within the part of Texas overseen by The Electric Reliability Council of Texas (ERCOT), there are now over "43,000 miles of transmission lines and 550 generation units" [16]. Each of these transmission lines and generation units must be represented accurately in the variety of models ERCOT and Texas power market participants use to make decisions about reliable and economic grid operation. Given the large complexity and impact of these models, there are significant opportunities for research that enhances, validates, or generates models in a way that improves grid operation decisions.

In response to this increasingly complexity, new methods of data collection are being investigated, including the increasing use of synchrophasors, or Phasor Measurement Units (PMUs). These devices, which provide enhanced measurements at a much higher sampling rate than conventional power system data collection, are being adopted throughout the North American power grid [1], as shown visually in Figure 1. In Texas, 94 PMU units have been installed within the ERCOT system [14].

This research investigates whether Bode analysis is a feasible method for generating dynamic system models using synthetic PMU data. Therefore, a background on synchrophasors and their potential uses within the North American power grid is provided, followed by an overview of current dynamic modeling techniques. Since the technique investigated in this paper involves linear models, special focus is given to an important linear model application, small-signal rotor stability. Finally, objectives for this work and ensuing research are presented.

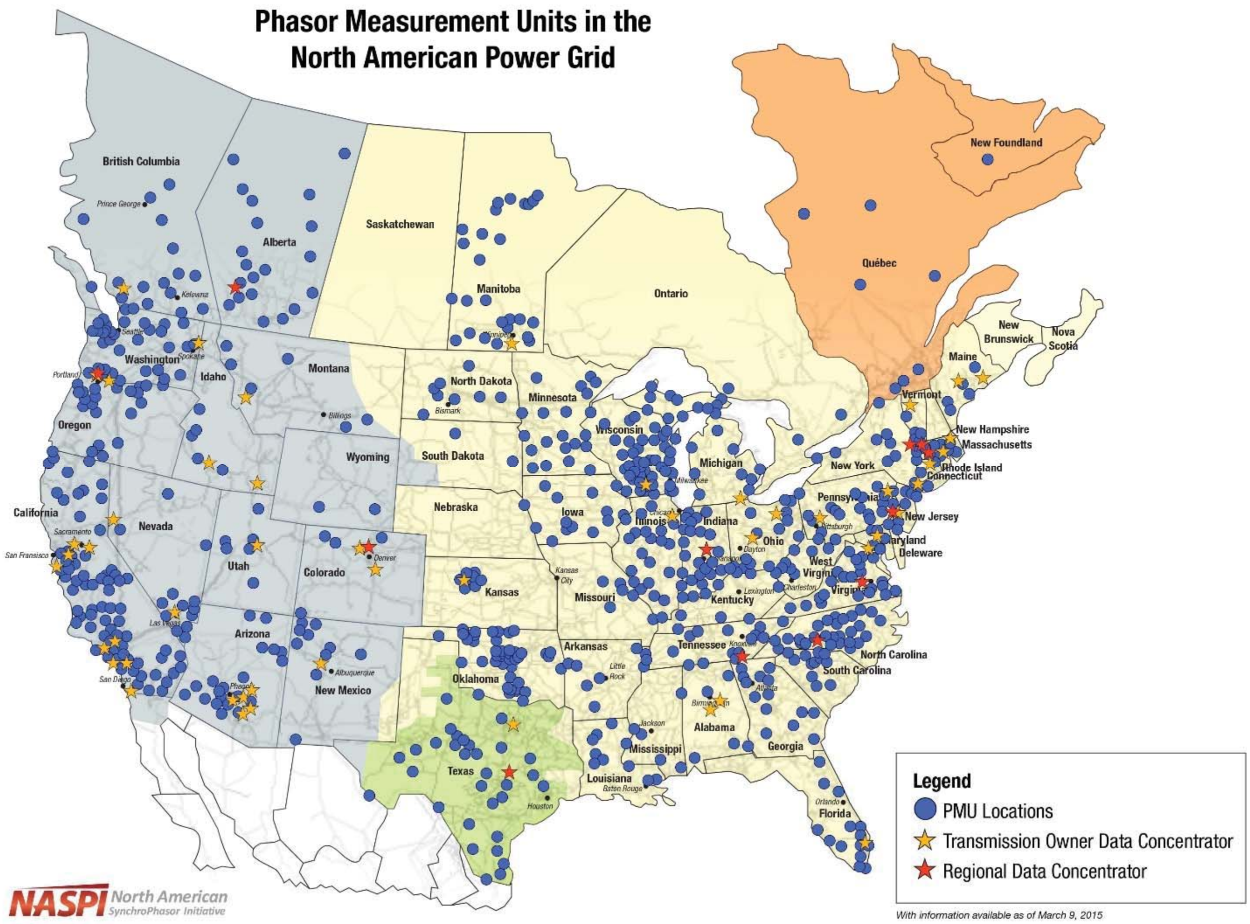

Figure 1: PMUs in the North American Power Grid, March 2015 [1]. Courtesy of the North American SynchroPhasor Initiative (www.naspi.org) and the U.S. Department of Energy.

Potential Uses for Synchrophasor Data in Power Systems

Function and advantages of synchrophasor technology

PMUs collect precise, time-stamped measurements from specific locations within the power grid [2]. These measurements include frequency, real power, and reactive power, as well as voltage and current magnitudes and phase angles. PMUs typically take at least 30 samples/second, a much higher rate than conventional grid monitoring technology. Thus, they require very sensitive time-stamping, made possible by GPS satellites.

The fast sampling rate and time synchronization of PMU data makes it possible to compare previously incomparable measurements within the power system, such as voltage phase angles between different geographic locations. As a result of advantages, PMUs are being adopted throughout the North American power grid, as shown in Figure 1.

Potential applications in power grid

A 2010 NERC report entitled "Real-time Applications of Synchrophasors for Improving Reliability" laid out a number of potential uses for PMUs in power system operation, and grouped them into three general categories [4]:

- "Applications to support real-time grid operations by providing wide-area visualization and increased state awareness."
- "Applications to improve system planning and analysis, including power system performance baselining, event analysis and model validation."
- "Response-based control applications that use real-time wide area information to take automated control actions on the power system."

The first category describes the functions of synchrophasors in alerting system operators to real-time system features, helping them to visualize the state of the grid and take corrective actions if needed [4]. Specific applications include general situational awareness, monitoring power, voltage, and frequency fluctuations, and detecting events such as line losses or line overloading. When serious oscillations or events occur, the PMU data can be processed and an alarm issued to system operators. Thus, if efficient methods are devised to process large amounts of PMU data, there is great potential to use this data to inform the human grid operators overseeing the system.

The second category relates to what is termed as “offline” procedures, namely carrying out the variety of studies needed generate system models and prepare for a variety of system events and operating conditions [4]. Results from these studies are used to plan for contingencies and determine expected deviations resulting from line or generator losses, as well as other events. PMU data could help to better inform these studies, and to validate current system models based on actual events, both on an individual component level and system-wide.

Unlike the first two categories, the third category discusses the use of synchrophasor data to make automatic computer-controlled decisions about grid operation [4]. The report notes that this is the least mature category of the three, but provides several potential applications, including Coordinated Secondary Voltage Control and Inter-Area Oscillation Damping Controls. Coordinated Secondary Voltage Control relates to scheduling voltage magnitudes at different grid locations such that there is an adequate reserve of reactive power. The idea of Inter-Area Oscillation Damping Control involves using PMU data to automatically take action to prevent phase angle oscillations between generators in different electrical areas of the system. While these applications could significantly increase the robustness of the power system, much research still must be done before these ideas are implemented [4].

While these applications are in various stages of development and implementation, it is clear that smart use of PMU data could greatly improve power system operation. Since this work focuses on Bode analysis, the next section focuses on linear dynamic models and related uses of synchrophasor data in Texas.

Overview of Dynamic System Modeling

Importance of dynamic system modeling in power systems

The main purpose of dynamical models is to help answer questions about power system stability, the ability of a system to reach and maintain an operating equilibrium point, even when subject to disturbances [3]. Since power systems are complex, stability problems—and the dynamical models used to describe them—are sorted into several different categories, including small-signal stability [3]. One critical area within small-signal stability, small-signal rotor stability, studies the impact of slight frequency and rotor angle deviations in synchronous generators [3]. Unwanted small oscillations in frequency and rotor angles in one or a group of generators can grow, potentially tripping off generators and causing havoc for the power system [3]. Thus, developing useful models to analyze small-signal rotor stability is imperative.

Attempts to incorporate PMU data

With a modeling scenario identified, past work in incorporating PMU data was studied. Various ways to integrate PMU data into stability assessment have been proposed for many stability problems, including fault detection and voltage stability margins [5,6]. However, for the small-signal rotor stability problem, research involving PMU data seems to be limited. Most of the existing research focuses on estimating some oscillatory information from the system [7,8], but the PMU data is not being used to improve or develop system models.

Using SMA to simplify dynamic system models

While no process was found that generated models directly from PMU data, a method was discovered that could take advantage of prior system knowledge: Selective Modal Analysis, or SMA [9-11]. Given an existing dynamical model, SMA allows for a reduced-order model preserving important oscillations, based on an understanding of which components are most strongly linked to those oscillations [9-11]. Assuming an approximate model exists, it appears there is strong potential to use PMU data and SMA to develop refined, simplified system models [12]. However, this work does not explore that potential.

Current model validation requirements

A three-hour panel was held at the July 2015 IEE PES General Meeting, providing information on current model validation techniques [13]. In this panel, numerous NERC and FERC guidelines on model verification were discussed, and it was apparent that model validation has recently been emphasized, both at the individual component level, such as a generator, and at the system level. Generator owners will soon be expected to validate their models, and transmission planners must provide a set of acceptable models. These models then must be periodically tested against real system data, and revised as needed. It is also recommended that these offline models be tested against models generated from real-time data, though it is not clear how these data-driven models will be generated [13].

In general, there appears to be a strong move towards periodic benchmarking of dynamic systems models, testing their output against actual system disturbances [13]. For a large system, this process seems to begin with looking at errors in the system-wide dynamic model and using those results to determine which system parameters need to be tuned. Also, since small-signal dynamic models linearize the power system around operating conditions, an emphasis is placed on ensuring dynamic models are updated as the system operating point varies.

ERCOT's use of PMU data in model validation

ERCOT, the Independent System Operator (ISO) for most of Texas, has been working to use post-event analysis of PMU from some of its 94 PMUs to validate dynamic generator models [14,15]. Approaches have been developed for both conventional synchronous generators and wind farms and were used to analyze an unexpected wind farm voltage oscillation event, helping to identify the root causes [15]. After some corrections for system operating conditions, PMU data was used to tune parameters within the existing dynamic model until the model output matched the observed PMU output. This process helped ERCOT to identify the voltage regulator settings of the wind farm as the primary culprit for the oscillations.

Although ERCOT continues to expand its use of PMU data in model validation and model parameter tuning, it does not currently have any plans to generate dynamic models strictly from PMU data, as recommended by NERC [13]. ERCOT also limits its model validation to post-event analysis, without considering the possibility of real-time model generation or parameter tuning.

Research Objectives

The overarching goal for my research is to develop better data-driven power system dynamical models. These models should be:

- Verifiable, using real-world power system data.
- Tunable, to account for the varying conditions in a real power system.
- Precise, with small confidence intervals in model output.
- Reliable, with the ability to adapt to many different operating conditions.
- Intuitive, with physical meaning that enables system control actions.
- Robust, acting to minimize the uncertainty of measurement and system noise.
- Practical, to be implemented in a real power system.

The hypothesis driving this research is that such models can be developed by combining prior system knowledge with PMU data.

CHAPTER II

MATHEMATICAL BACKGROUND

To evaluate whether Bode analysis is a reasonable power system modeling technique, I will present and analyze a series of test cases using MATLAB and Simulink software. This chapter presents background to explain the mathematical concepts applied in these test cases.

Classical Linear System Theory and Bode Analysis

This section explores mathematical theory related to a single-input, single-output (SISO) system [17]. Such a system F of order n can be represented as a state-space model by

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \tag{II.1}$$

$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u} \tag{II.2}$$

and can be modeled as a transfer function by

$$\mathbf{y} = \mathbf{G}\mathbf{u}. \tag{II.3}$$

In classical linear system theory, system input is labeled $\mathbf{u}$ and its output is labeled $\mathbf{y}$. By definition in a SISO system, both $\mathbf{u}$ and $\mathbf{y}$ are scalars. While $\mathbf{u}$ and $\mathbf{y}$ can certainly be complex numbers, this analysis assumes that $\mathbf{u}$ and $\mathbf{y}$ are real numbers.

In state-space representation, the relationship between $\mathbf{u}$ and $\mathbf{y}$ is mediated by n state-space variables contained in the $\mathbf{x}$ matrix [17]. The derivatives of these variables, $\dot{\mathbf{x}}$, is represented as a linear combination of the state-space variables and input $\mathbf{u}$, as modified by matrices $\mathbf{A}$ and $\mathbf{B}$. The output $\mathbf{y}$ is also determined by a linear combination of the state-space variables, and the input $\mathbf{u}$. However, in this analysis, it is assumed there is no direct throughput between $\mathbf{u}$ and $\mathbf{y}$, so $\mathbf{D}$ is set to 0.

Through Bode analysis, open-loop frequency plots of system magnitude and phase can be generated. The fundamental concept of Bode analysis holds that a sinusoidal input at a given frequency will result in a steady-state output sine wave with a set multiplication factor and a constant added phase shift [17]. The corresponding multiplication factors and phase shifts can then be plotted against frequency. These graphs are known as Bode magnitude and phase plots respectively, and the frequency and amplitude components are often plotted in a log scale. When amplitude is represented as logarithm, its unit is called a decibel, abbreviated dB.

Once Bode plots are generated for a system, a transfer function can be easily estimated. This property stems from only one pair of magnitude and phase Bode plots corresponding to one open-loop transfer function **G**, and the impossibility for two distinct open-loop transfer functions to correspond to the same Bode plots [17]. Thus, it seems feasible to generate transfer function models from Bode analysis of a power system.

One problem arises in comparing state-space and transfer function models: a single transfer function model can be represented by an infinite number of state-space models [17]. Thus, even if it is feasible to generate transfer function models from Bode analysis, it may prove difficult to adequately compare transfer function models with available state-space models. One solution would be to start with some initial state-space model of the system, and use the Bode analysis results to validate the state-space model and tune key system parameters.

Linear Filtering Concepts

The purpose of a linear filter is to map a signal, in the form of a piecewise continuous function f, into another signal $\tilde{f}$ [18]. Such a filter is linear when it satisfies additivity and homogeneity:

$$Additivity : L[f+g] = L[f] + L[g] \tag{II.4}$$

$$Homogeneity : L[cF] = c * L[f], \tag{II.5}$$

where f and g are signals, and c is a constant [18].

In this work, such filters will be used to separate a set of specific target frequencies by using a narrow pass band. To accomplish this feat, a MATLAB implementation of finite impulse response (FIR) and infinite impulse response (IIR) filters will be utilized. Though there are important differences between the two types, especially in physical implementation, they will be used interchangeably for the same purpose here. When implementing band-pass filters using MATLAB's designfilt command, four key parameters must be set: the lower stopband frequency, the lower passband frequency, the upper passband frequency, and the upper stopband frequency [19]. These parameters define the bands that will be passed and stopped by the filter, as well as the small zones between the passband and the stopbands [19]. Additionally, the stopband attenuation factor and the passband ripple must be set. These features correspond to the amount of attenuation applied to the stop band and the amount of amplitude ripple in the bands passed through the filter. If there is too much of a passband ripple, then the amplitude relationships among the frequencies in the passband will be distorted [19].

One drawback of such filtering is that, even with high quality FIR and IIR filters, there will still be an amplitude multiplier and induced phase shift at a given frequency [19]. However, this problem can be avoided when creating Bode plots by subjecting both the input and output to the same filter before taking the ratios of their amplitudes and comparing phase shifts. If we assume the inputs and outputs are sine waves of a uniform frequency, we can represent them as phasors with form

$$A\angle\phi, \tag{II.6}$$

where A is the magnitude of the phase shift and ϕ is the shift angle.

If the linear filter induces a magnitude shift b and phase shift ϕ_{shift} to both the phasor input and the phasor output, then the ratio of these phasors generates a new phasor with

$$Magnitude : \frac{b * A_{output}}{b * A_{input}} = \frac{A_{output}}{A_{input}} \tag{II.7}$$

$$Phase : (\phi_{out} + \phi_{shift}) - (\phi_{in} + \phi_{shift}) = \phi_{out} - \phi_{in}, \tag{II.8}$$

which corresponds to the correct Bode magnitude and phase ratios between input and output. Therefore, the filtered input and output can be directly compared at each frequency to construct the Bode plots.

Fast Fourier Transform

The Fast Fourier Transform (FFT) is a special case of the Discrete Fourier Transform (DFT) in which a more efficient calculation algorithm is used [18]. The DFT is itself a special form of the Fourier Transform applied to a sampled, rather than continuous, signal [18]. Since the computation algorithm is not of importance in this work, this section will focus on providing an intuitive understanding of the DFT and FFT and how they can be converted to produce a single-sided frequency spectrum for a signal.

The definition of the DFT is given by [18]:

$$\hat{y}_k = \sum_{j=0}^{n-1} y_j * \bar{w}^{jk}, \tag{II.9}$$

where $\bar{w}$ relates to the angular frequency, scaled by a width factor related to the number of samples and current sample number. The sequence $\hat{y}_k$ represents the transformed values of the sampled time signal y_j into the frequency domain.

This set of values and their frequency components $\bar{w}$ can then be plotted to obtain an estimate of the two-sided frequency spectrum of the signal y. This plot will be accurate for frequencies which are much lower than the sampling rate [18]. For a real-valued sample, this two-sided frequency spectrum will by symmetric around its center and contain both positive and negative frequency values [20]. This sample can then be converted to a single-sided power spectrum by cutting it in half (to limit to positive frequencies) and by multiplying the remaining $\hat{y}_k$ values by 2 [18,20]. The amplitude spectrum can then be generated by taking square root of the power spectrum values at each frequency.

Once a one-sided amplitude spectrum is generated for system input and output composed of a sum of sinusoids, the Bode amplitude plot can be generated by taking a ratio of input and output magnitudes at each frequency.

White Noise

White noise is a collection of random random variables with a constant power spectral density [21,22]. It receives special attention in this work, because it is assumed that the deviations from equilibrium present in standard power system operation can be modeled as white noise. Since unbounded white noise would have infinite power, this work deals with band-limited white noise, with a large band that covers all frequency ranges of interest [21].

Signal-to-Noise Ratio

The Signal-to-Noise-Ratio (SNR) is defined as the ratio of the desired signal's power to the power of the unwanted noise [23]:

$$SNR = \frac{Power_{signal}}{Power_{noise}}, \tag{II.10}$$

where power is tied to the square of the signal amplitudes.

SNR is useful for roughly assessing the amount of noise present in the system, and will be used to quantify the effects of noise on the results of Bode analysis.

Kalman Filtering

A Kalman Filter will be used to attempt to account for the effects of white noise present in the system on the results of Bode analysis. Therefore, some background is provided to describe the basic functions of Kalman Filtering, knowledge required to implement the Kalman Filter, and some key equations.

The function of a linear Kalman Filter is to estimate the current state of a system from noisy data, and predict noise-free output measurements [24]. This estimation is achieved recursively, and intended to optimize the parameters to optimize the least squares error in the face of Gaussian white noise [24]. It is assumed a state-space model of the system exists in the form of (II.1) and (II.2), with a new form to account for noise:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} + \mathbf{V} \tag{II.11}$$

$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{W}, \tag{II.12}$$

where W and V represent the contributions from measurement and process white noise, respectively [24]. When discretized to account for a finite sampling rate, the equations appears in the form [24]:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{V}(k) \tag{II.13}$$

$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) \tag{II.14}$$

$$\mathbf{z}(k) = \mathbf{C}\mathbf{x}(k) + \mathbf{W}(k), \tag{II.15}$$

where $\mathbf{z}(k)$ is the observed measurement for sample k. When a new sample arrives, the estimate of the system state is adjusted according to the equation [24]:

$$\mathbf{x}(k+1|k+1) = \mathbf{x}(k+1|k) + \mathbf{W}(k+1)\mathbf{V}(k+1), \tag{II.16}$$

where $\mathbf{V}(k+1)$ is the measurement residual given by [24]:

$$\mathbf{V}(k+1) = \mathbf{z}(k+1)\mathbf{z}(k+1|k). \tag{II.17}$$

Then, $\mathbf{W}(k+1)$ is termed the Kalman Filter gain [24], which determined at each step by applying knowledge about noise, state and prediction error covariance [24].

Therefore, to implement Kalman Filtering, there must be an existing state-space system model and knowledge about the covariance of process and measurement noises [24]. In this work, it is assumed that these noise covariances are known.

CHAPTER III

METHODS

Starting with a simplistic preliminary test case, a series of increasingly complex approaches are proposed to generate accurate system magnitude and phase Bode plots in MATLAB using synthetic system data from Simulink. Keeping in mind the small signal rotor stability problem [3], all the generated Bode magnitude and phase plots target from 0.1-2 Hz.

Preliminary Test Case

Using linear system theory, it should be possible to generate system Bode plots from applying a sine wave input with known amplitude and phase and observing the amplitude and phase of the resulting steady-state output sine wave [17]. If this process is repeated at given frequency intervals, an estimate of the system Bode phase and magnitude plots should be generated.

To test this theory, a simple transfer function system model was constructed in Simulink. A series of 19 sine wave inputs was applied, with frequencies from 0.1 to 2 Hz and a step size of 0.1 Hz. The resulting output sine wave were observed on the oscilloscope, and the phase angle and amplitude shifts were recorded. These results were then used to generate Bode magnitude and phase plots presented in the Results section.

Description of the Test System

In all cases but the single sine wave method, the system used to generate data is a 4-generator, 28^{th} order, linearized, state-space MATLAB model. Each generator was represented by a 7th-order dynamic model, without considering dynamics from other components in the system. The system was linearized around an operating point, and input and output data was sampled at 60 Hz. The system input was the generator 1 voltage regulator setpoint, and the system output was the bus frequency at generator 1.

This model was developed by former Texas A&M graduate student Yang Chen, and used in [12]. It is shown visually in Figure 2.

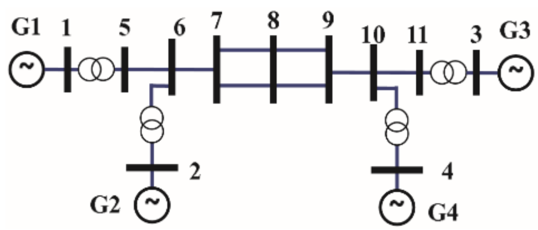

Figure 2: Diagram of the Test System

Test Cases

Case 1: Bode Analysis Using 19 Sine Waves

This approach carries out Bode plot generation in "one shot" by applying a summation of sine waves of many different frequencies to the system. The system input and output are then filtered by frequency and compared to generate the magnitude and phase Bode plots. Since the filters are linear and the same filter is applied to both the input and output for a given frequency, the phase shift and amplitude ratio imparted by each filter should not affect the accuracy of the Bode plot.

To test this theory, sine waves of frequencies from 0.1-2 Hz were generated at 0.1 Hz intervals and summed in Simulink. The resulting function of 19 sine waves was then selected as input for the 28th order system. After simulating the system in Simulink for 10,000 seconds, an output waveform was obtained, and both the input and output waveforms were filtered for each frequency step in MATLAB using FIR filters. The amplitude ratios and phase shifts at each frequency were then compared and utilized to generate system Bode plots.

Figure 3 presents a diagram summarizing the process, and Figure 4 presents a visual overview of the system in Simulink. Please note that the transfer function model is a converted version of the 28^{th} order state-space model, and both produced the same output.

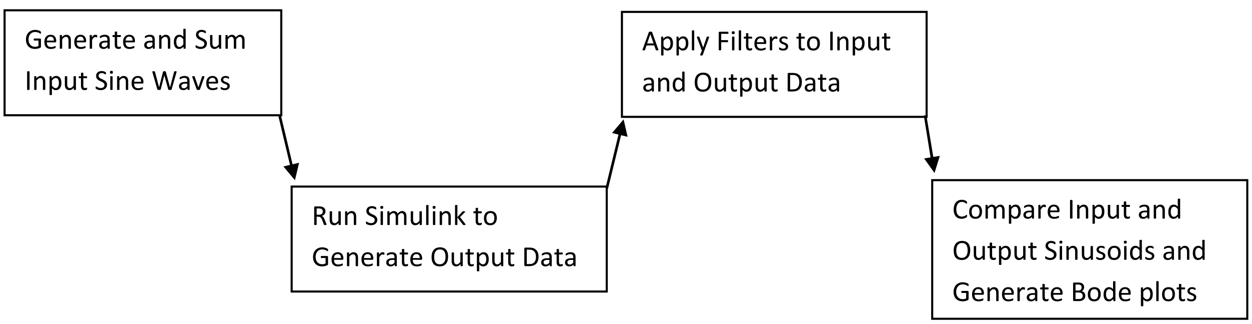

Figure 3: Visual Diagram for Bode Analysis Using 19 Input Sine Waves

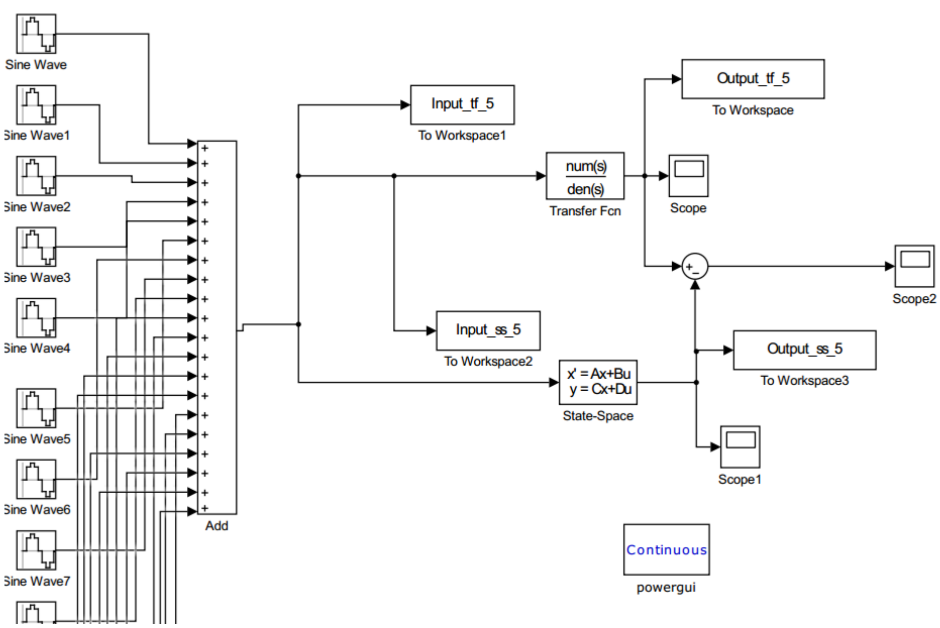

Figure 4: Simulink Implementation of 19 Sine Waves Technique

Case 2: Bode Analysis Using 191 Sine Waves

The process described in the previous subsection was repeated for sine waves from 0.1-2 Hz at 0.01 Hz intervals, generating 191 sine waves and 191 discrete points on the Bode plot. Only small changes were made in implementation, including the use of IIR filters to improve calculation time and the method by which the input was generated. Instead of generating and summing the sine waves in Simulink, they were summed in MATLAB and imported to Simulink. Figure 5 displays the structure of the system in Simulink.

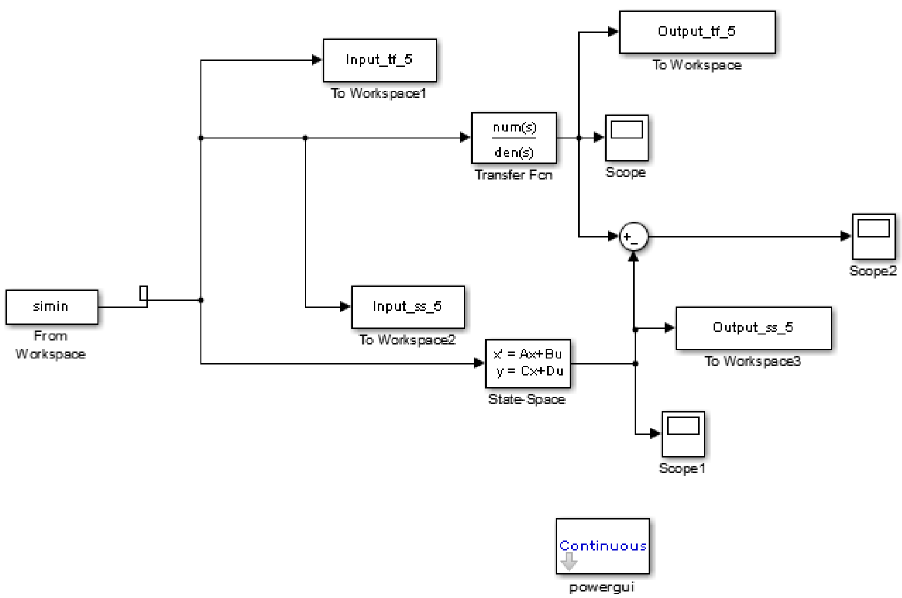

Figure 5: Simulink Implementation of 191 Sine Waves Technique

Case 3: Bode Analysis Using White Noise with Sum of Sine Waves Method

To examine the effect of white noise on the Bode analysis results, the Case 2 method was repeated, but with the input sum of sinusoids replaced by bandlimited white noise. Since the simulation was being carried out for a reasonably long time, it was hoped that the variations within the white noise would average out and a reasonably accurate Bode plot could be obtained. Figure 6 shows the Simulink configuration used to implement this test case.

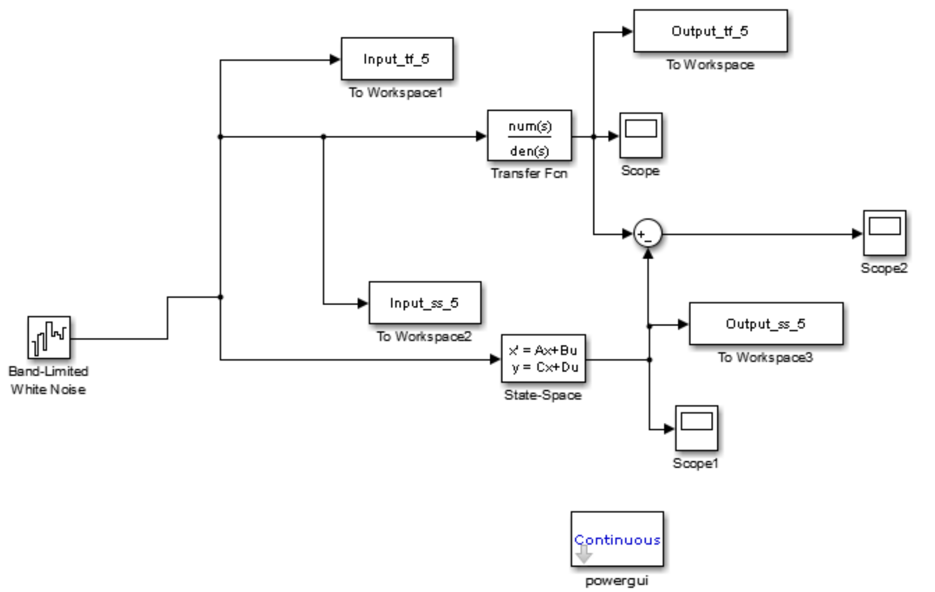

Figure 6: Simulink Implementation of Test Case 3

Case 4: Bode Analysis Using White Noise with FFT

Executed in parallel with Case 3, Case 4 had the same goal: examine the effect of a white noise input on the Bode analysis results. However, this test case focused on the Bode magnitude plot, and implemented an alternative way to generate it using the FFT. As described in the Mathematical Background, the FFT can be used to generate an amplitude spectrum for a signal, and can easily be applied in MATLAB to both the system input and output signals. Then, the ratio of the output and input amplitudes for each frequency can be compared to generate a Bode magnitude plot. Figure 7 shows a graphical overview of this process, and Figure 8 shows the Simulink implementation.

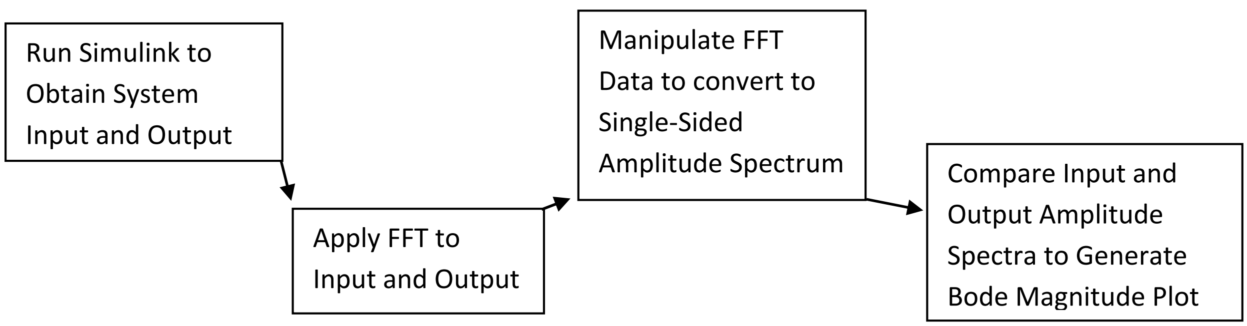

Figure 7: Visual Diagram for Bode Analysis Using FFT and White Noise Input

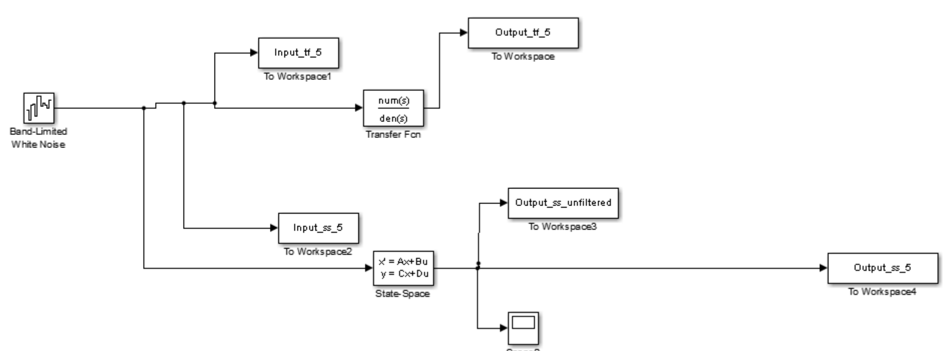

Figure 8: Simulink Implementation of Test Case 4

Case 5: Observing Effect of Output Noise on Bode Results

To investigate the effect of output noise on Bode plot accuracy, the Case 2 sine wave method was repeated for 2 different SNR levels, 42.4% and 4.24%. The resulting Bode plots for each case should highlight whether Bode analysis is suitable for an environment where introducing oscillations is unhealthy and a small SNR, ideally less than 1%, is required.

Case 6: Applying Kalman Filtering with 191 Sine Waves Technique and Output Noise

In this test case, the Case 2 sine wave method was repeated, but now with additive white noise at the output and a Kalman Filter. It was assumed that output noise variance was known, so the only parameter being manipulated was the choice of estimated system model. Two estimated system models were used: one was the accurate 28th-order model, and the other was an inaccurate estimated model. Figure 9 shows the configuration for this test case in Simulink.

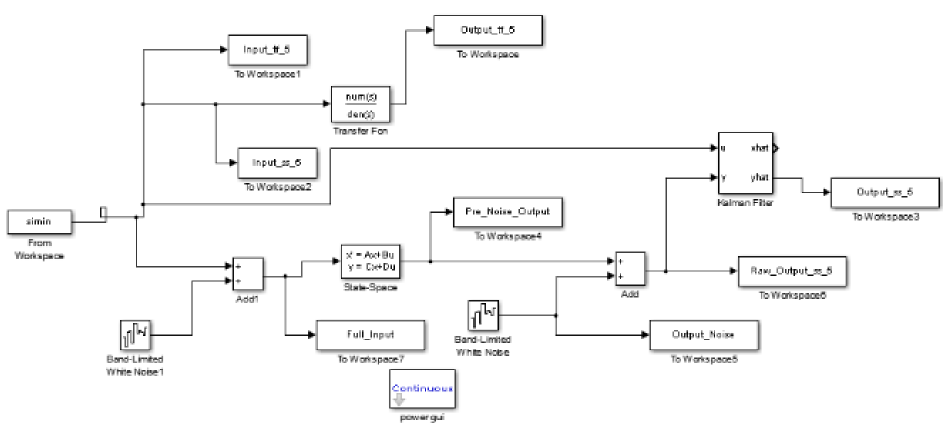

Figure 9: Simulink Implementation of Test Case 5

CHAPTER IV

RESULTS

Test Case Results

Preliminary Test Case

The results for the preliminary test case are shown graphically in Figures 10 and 11. Though there is some slight random error due to reading off the Simulink oscilloscope, the dots associated with the estimated values match up well with the actually Bode magnitude and phase plots.

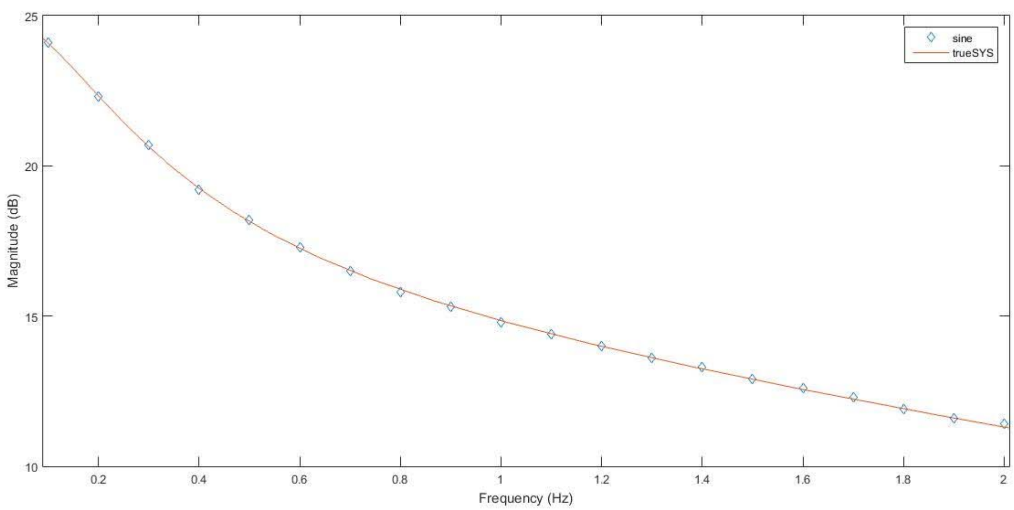

Figure 10: Bode Magnitude Plot for Preliminary Test Case

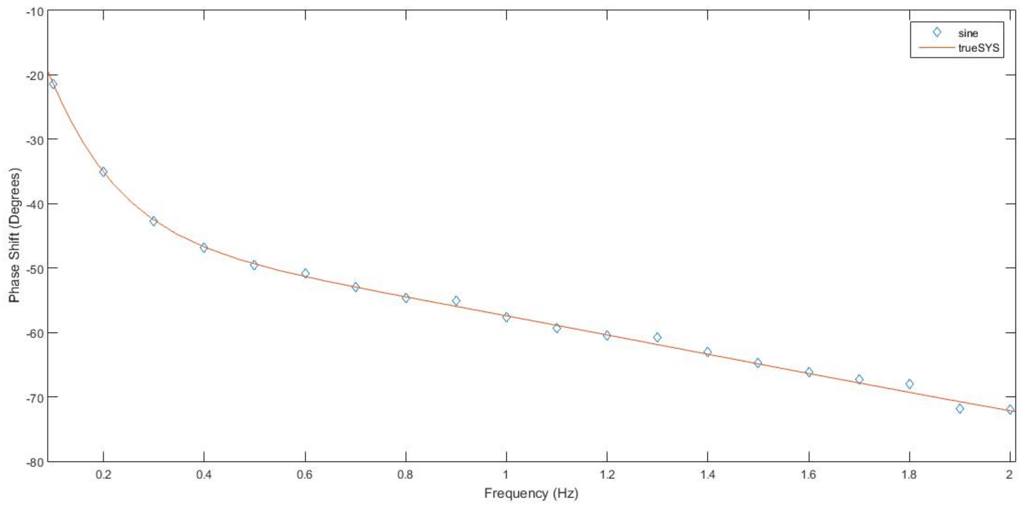

Figure 11: Bode Phase Plot for Preliminary Test Case

Case 1: Bode Analysis Using 19 Sine Waves

The results for the Case 1 are shown visually in Figures 12 and 13. The results of Bode analysis again match up well with the true system, with much less error than was associated with reading off the oscilloscope for the preliminary test case.

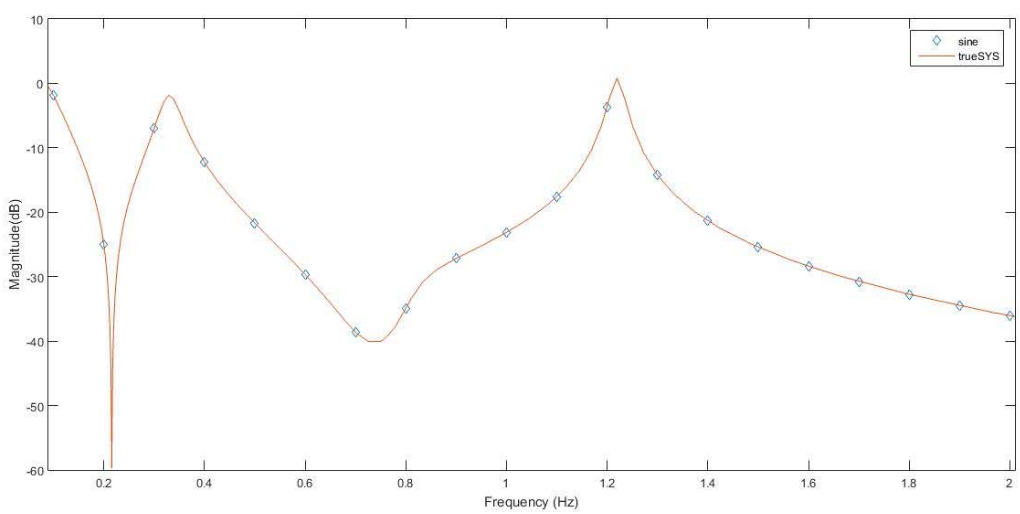

Figure 12: Bode Magnitude Plot for Case 1

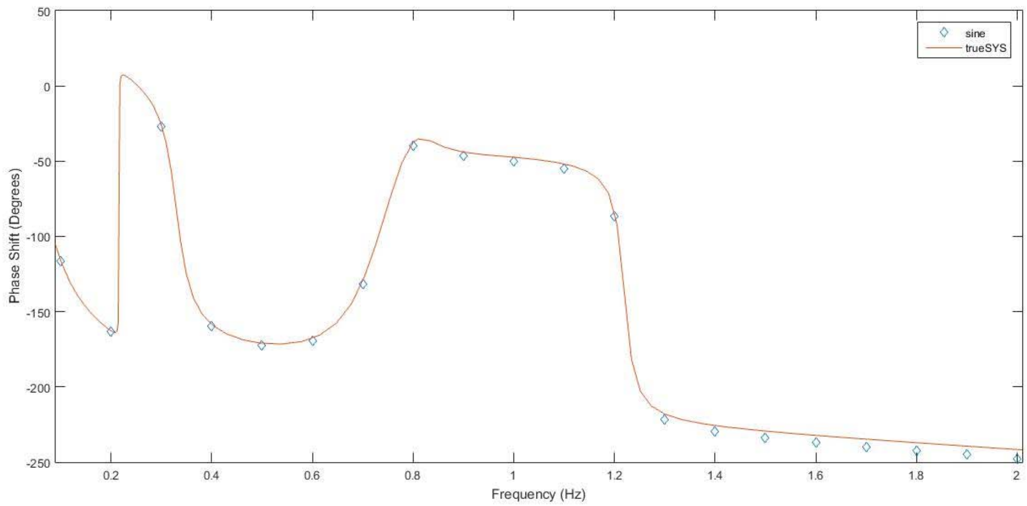

Figure 13: Bode Phase Plot for Case 1

Case 2: Bode Analysis Using 191 Sine Waves

The results for the Case 2 are presented graphically in Figures 14-16. Again, and this time with a much higher definition, the Bode analysis results match the true system. Also, the measured phase jumps 360°, and must be corrected.

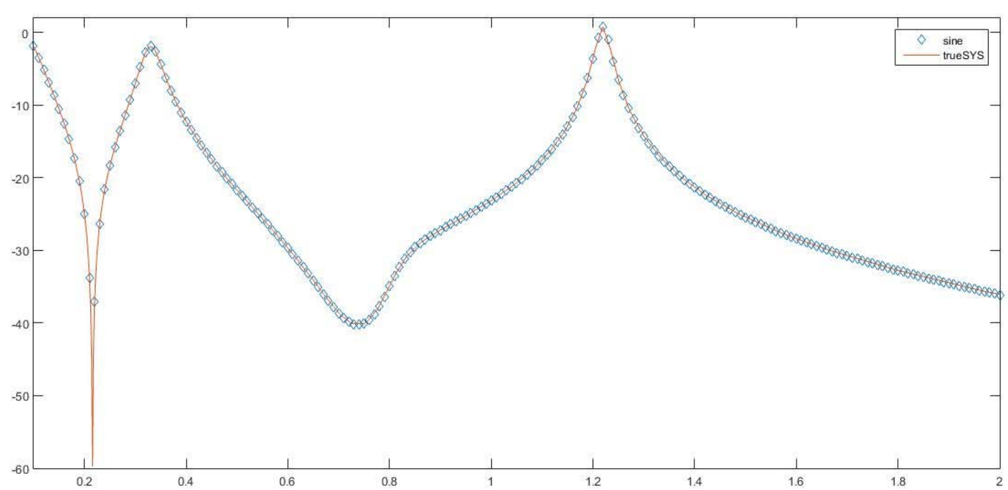

Figure 14: Bode Magnitude Plot for Case 2

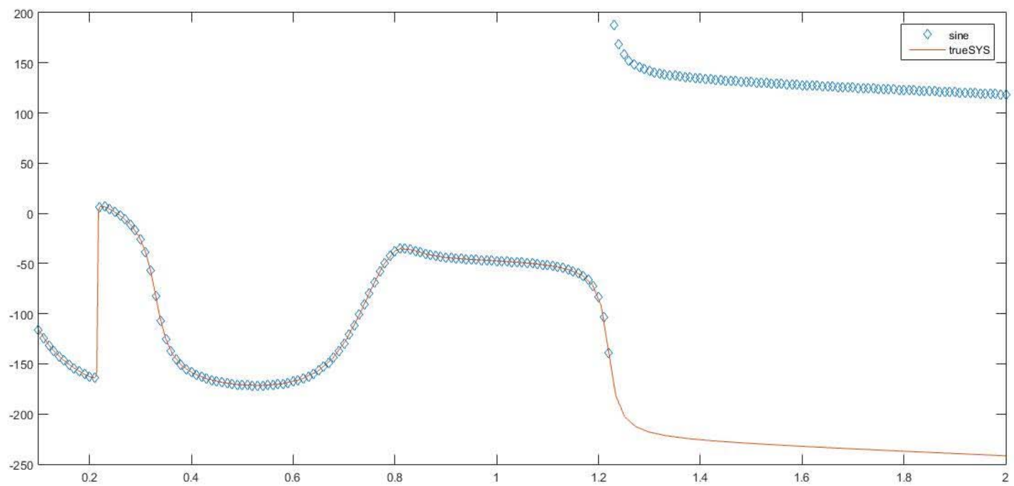

Figure 15: Bode Phase Plot for Case 2

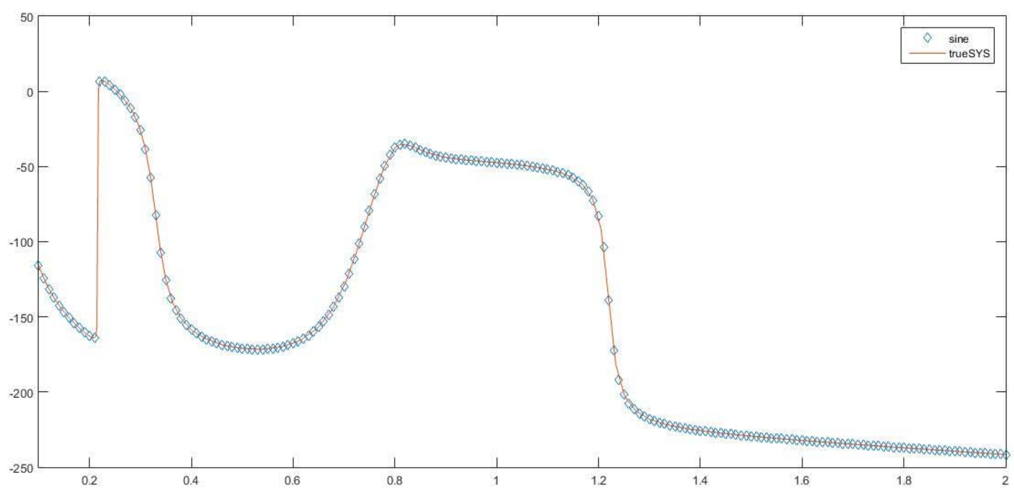

Figure 16: Bode Phase Plot for Case 2 (Adjusted for 360° Phase Jump)

Case 3: Bode Analysis Using White Noise with Sum of Sine Waves Method

When white noise is applied as an input in Case 3, the estimated Bode plots no longer accurately match the true system Bode plots, as shown in Figures 17 and 18. Though the estimated magnitude plot does shadow the shape of the true system magnitude plot, it has a significant dB offset that indicates a major multiplication scaling factor. Thus, this result is not useful.

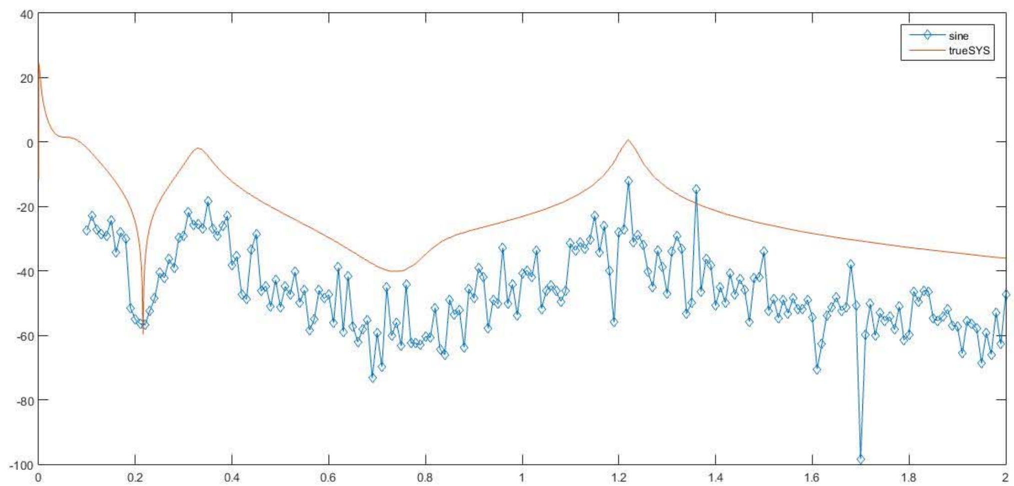

Figure 17: Estimated Bode Magnitude Plot for Case 3

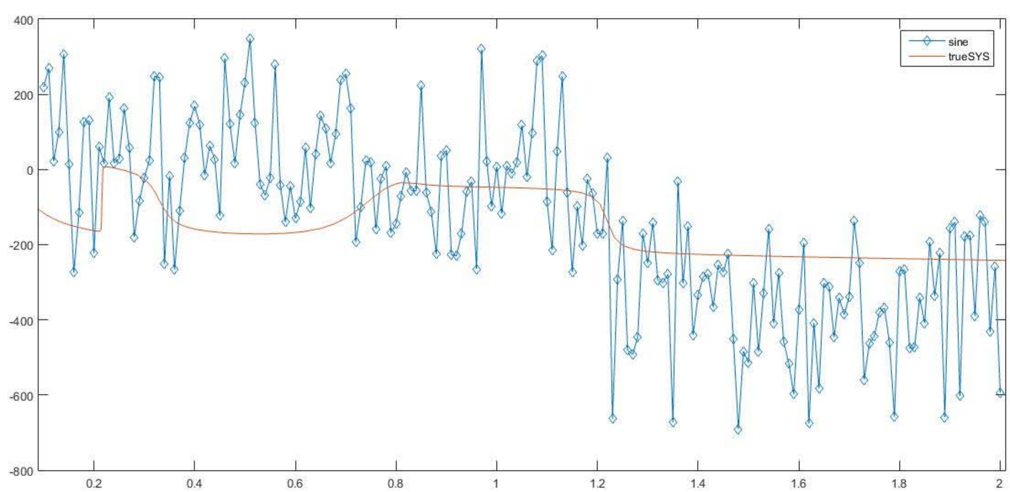

Figure 18: Estimated Bode Phase Plot for Case 3

Case 4: Bode Analysis Using White Noise with FFT

When white noise is applied as an input, the estimated Bode magnitude plot does not match the true system plot, as shown in Figure 19. As in Case 3, the estimated magnitude plot noisily shadows the shape of the true system magnitude plot, but with a significant dB offset. This result indicates a major multiplication scaling factor issue, and this method is not practical.

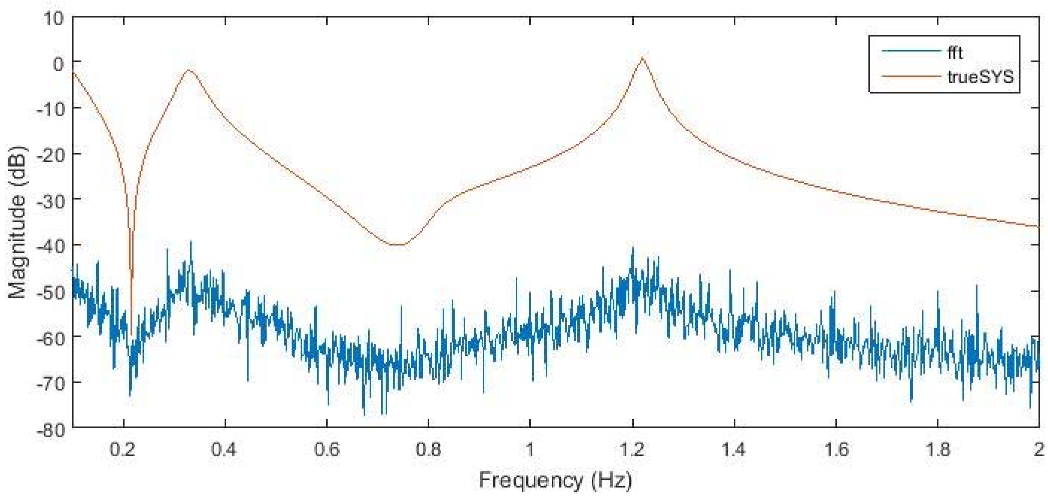

Figure 19: Estimated Bode Magnitude Plot for Case 4

Case 5: Observing Effect of Output Noise on Bode Results

The visual results from this experiment are shown in Figures 20-23. With a 42% SNR, the Bode plots are little changed. However, when the SNR drops to 4.2%, there is significant distortion of the magnitude plot, especially in the more attenuated regions, and the phase plot becomes unreliably jumpy. Since I do not want to inject large oscillations into the power system, I would want a good approximation of the Bode plots for an SNR of less than 1%. The observed result does not meet this requirement.

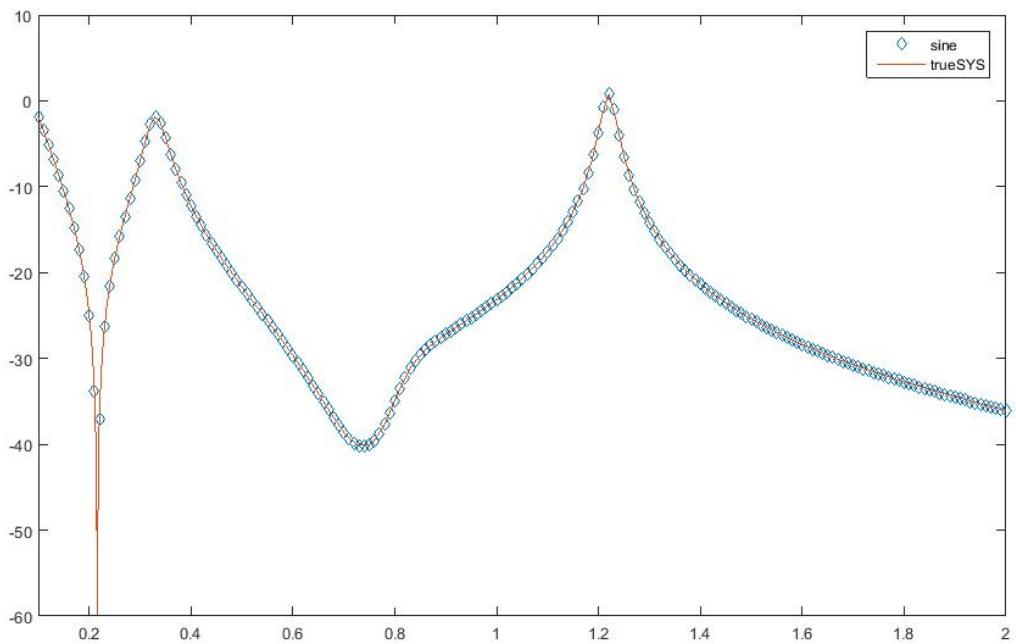

Figure 20: Effect of 40% SNR on Bode Magnitude Plot

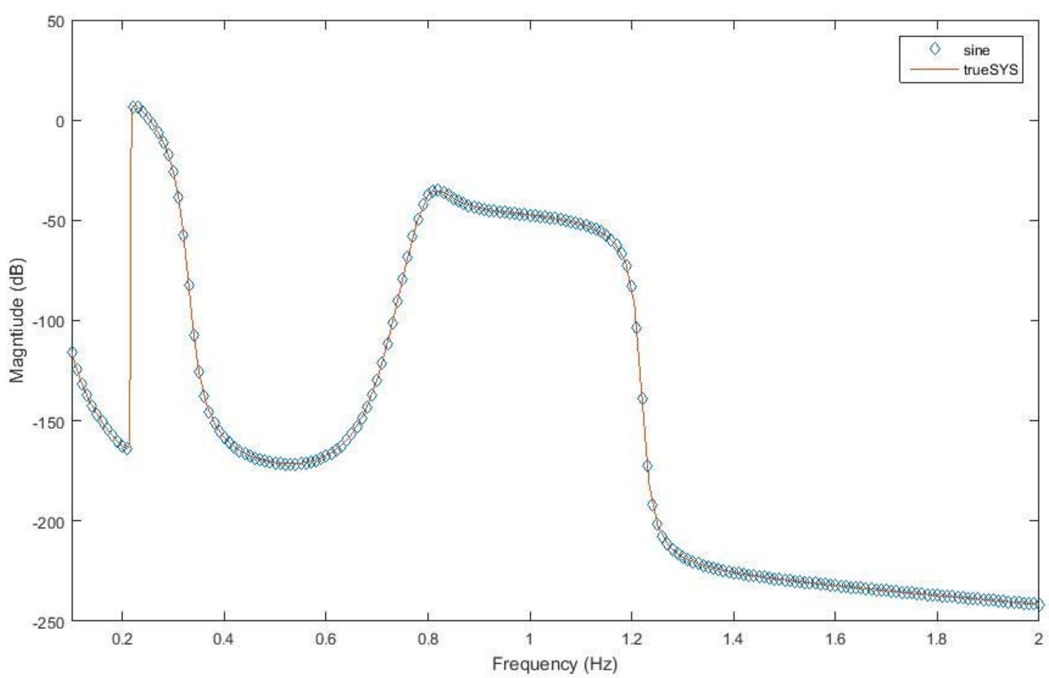

Figure 21: Effect of 40% SNR on Bode Phase Plot

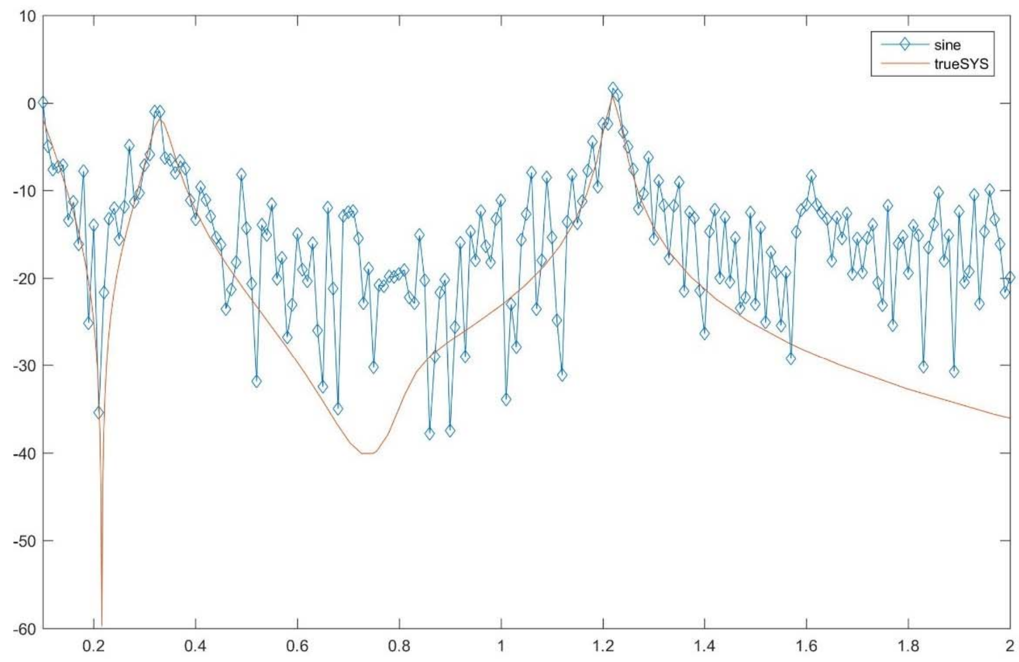

Figure 22: Effect of 4% SNR on Bode Magnitude Plot

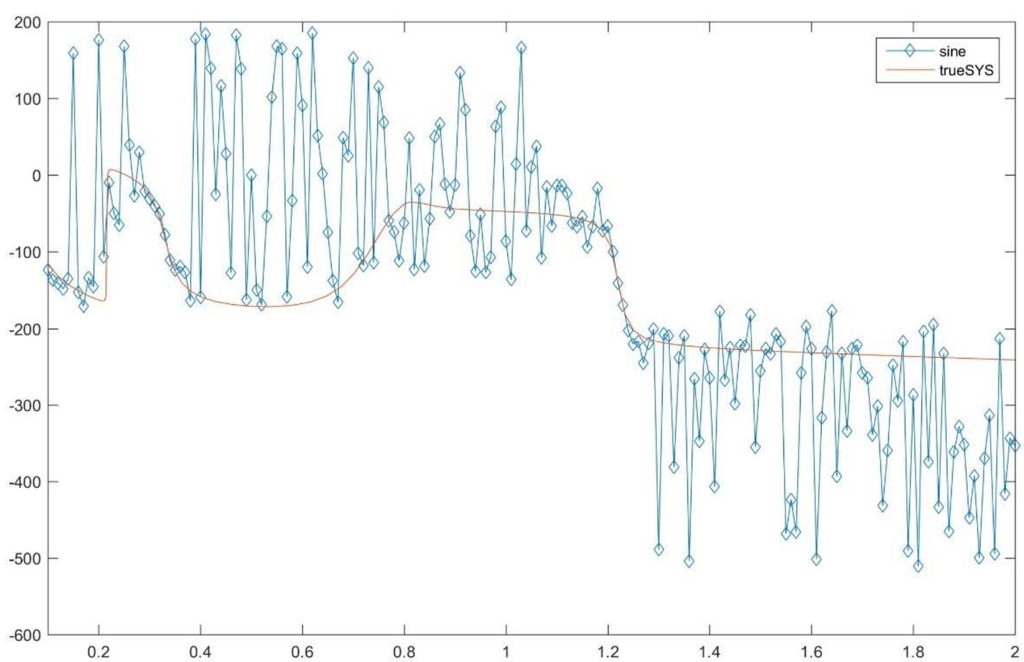

Figure 23: Effect of 4% SNR on Bode Phase Plot

Case 6: Applying Kalman Filtering with 191 Sine Waves Technique and Output Noise

Figures 24-27 visually demonstrate the results from applying a Kalman filter with a perfect system model and an imperfect system model. While the ideal model case results are ambiguous, the results from the imperfect system model case indicate the sine wave method converges to the Bode plot of the chosen model, not the true system. Thus, no knowledge is gained from performing Bode analysis with output noise and a Kalman Filter.

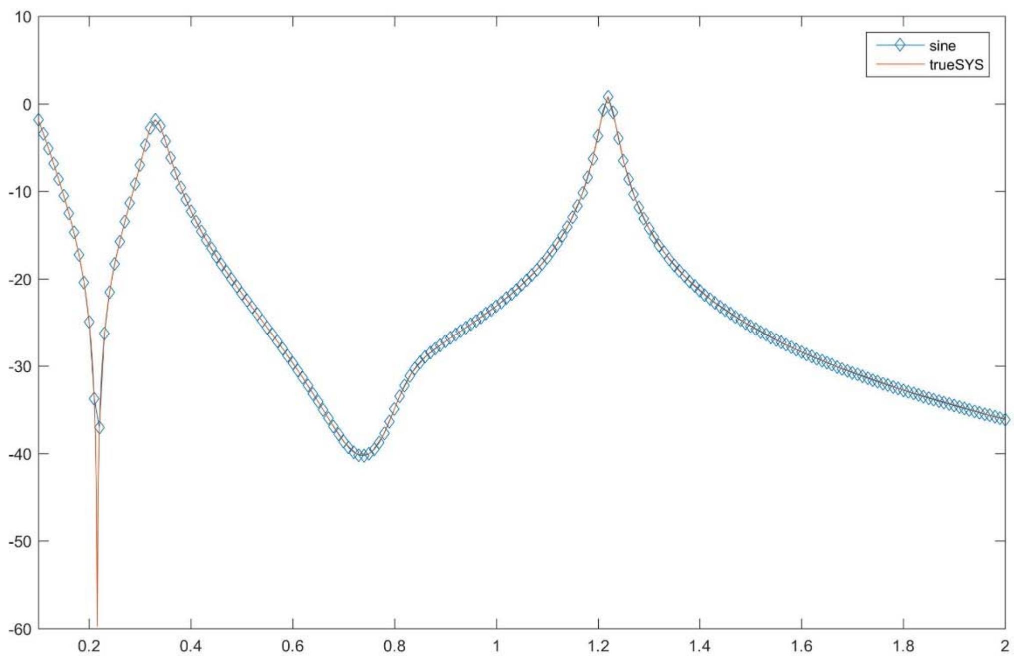

Figure 24: Kalman Filtering with Perfect System Model Bode Magnitude Plot

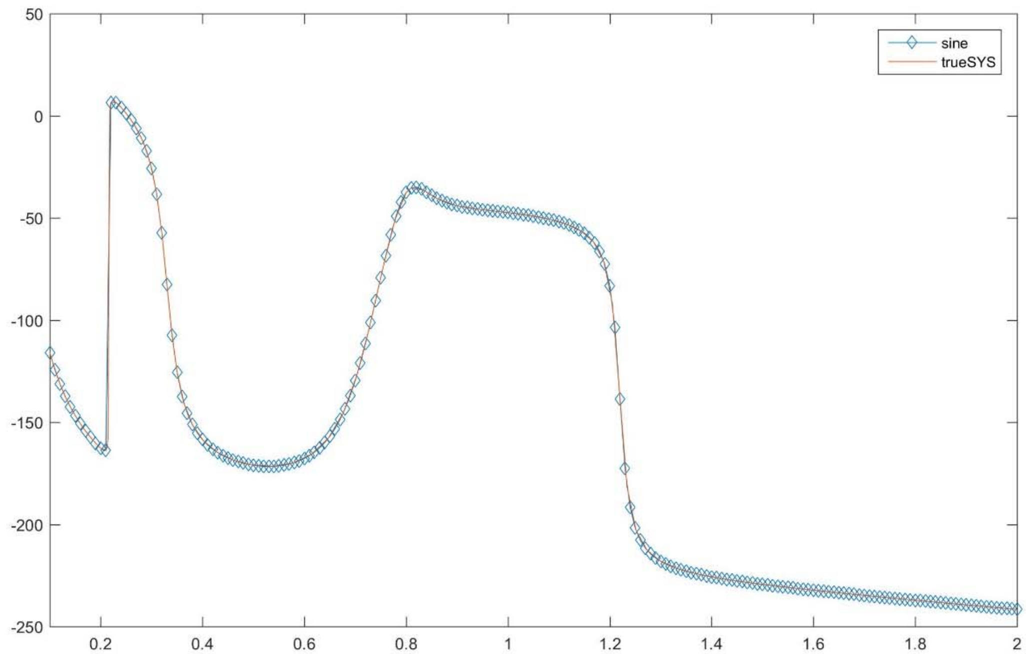

Figure 25: Kalman Filtering with Perfect System Model Bode Phase Plot

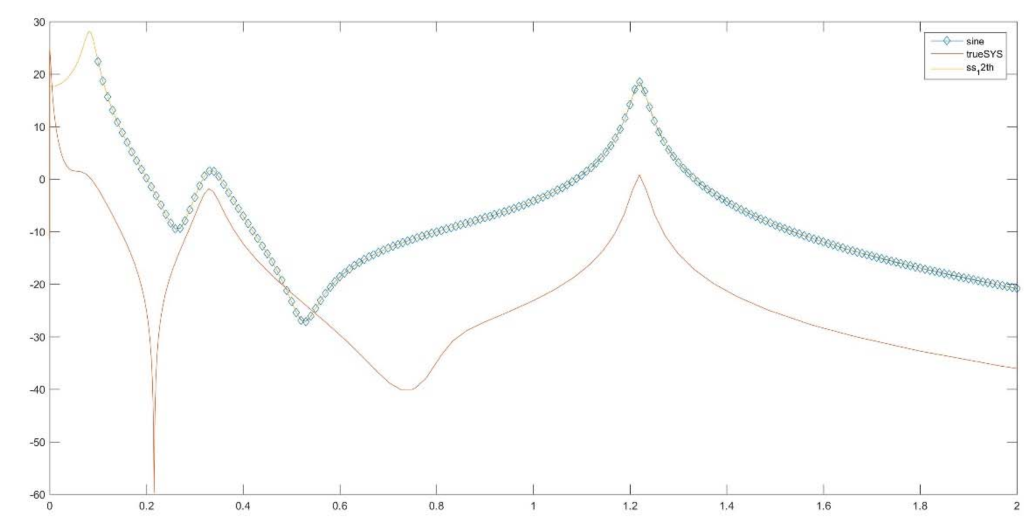

Figure 26: Kalman Filtering with Imperfect System Model Bode Magnitude Plot

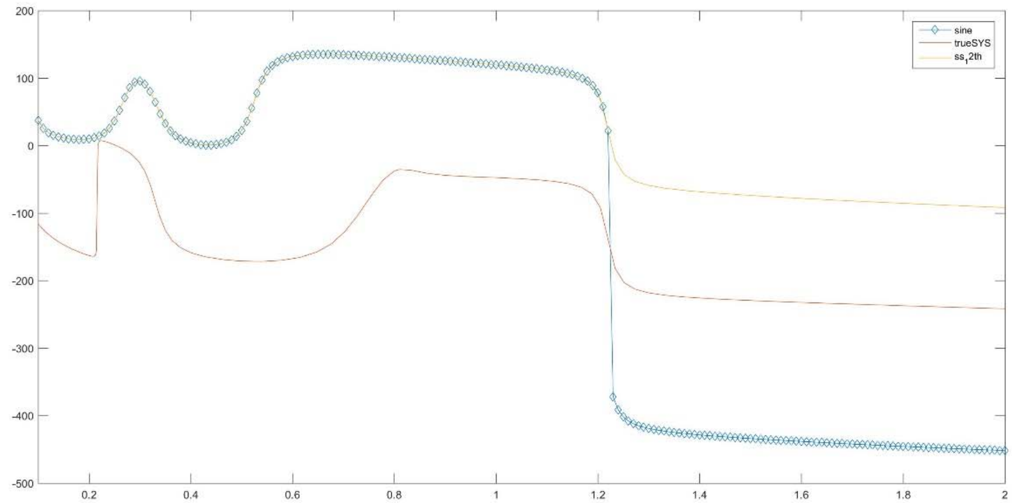

Figure 27: Kalman Filtering with Imperfect System Model Bode Phase Plot

CHAPTER V

CONCLUSION

Analysis of Results and Proposed Next Steps

Despite some positive results, it is clear that Bode analysis is not a good technique to generate practical power system dynamic models. While accurate Bode plots could be generated in cases with no system noise, results were very poor in more practical systems with a low SNR ratio. In cases with a pure white noise input, my experiments demonstrated that accurate Bode magnitude or phase plots could not be generated by comparing the amplitudes and phases of input data with output data. In cases with output noise, a small amplitude input, and Kalman Filtering, it was demonstrated that the Bode plot results converged to the test system used in the Kalman filter, not to the true test system.

Therefore, I will no longer pursue Bode analysis as a method for generating and tuning dynamic models. Instead, my future work will investigate model identification methods more resilient to system noise, including recursive parallel, equation error, and output error methods. Once effective modeling techniques are identified for linear systems, I will consider methods for modeling non-linear systems, and investigate the possibility of online parameter tuning for generators and other system components. To carry out this research, I will continue working with MATLAB, Simulink, and the System Identification Toolbox, and will study programming languages such as Python. I remain convinced that there is great opportunity to generate and validate dynamic system models in real time, and my future work will continue to pursue this goal.

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