System Identification Tools for Power Systems Using Synchronized Measurements

Final Project Report

S-97G

Power Systems Engineering Research Center
Empowering Minds to Engineer
the Future Electric Energy System

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Project Team
Vaithianathan (Mani) Venkatasubramanian, Project Leader
Washington State University

Graduate Students
Saugat Ghimire
Habib Wajid

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For information about this project, contact:

Vaithianathan (Mani) Venkatasubramanian
Professor, School of Electrical Engineering and Computer Science
Washington State University
Email: mani@wsu.edu

Power Systems Engineering Research Center

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For additional information, contact:

Power Systems Engineering Research Center
Arizona State University
527 Engineering Research Center
Tempe, Arizona 85287-5706
Phone: 480-965-1643

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Executive Summary

With large-scale integrations of renewable energy sources, the dynamics of the power systems are becoming more complex in power grids all over the world. Fast dynamic controls and switches that are built into the newer power electronic based energy interfaces are interacting with the traditional power grid controls in unpredictable ways. These complex and non-smooth dynamic mechanisms are impacting on the small-signal and transient stability properties of bulk power systems. This project focused on the development of novel system identification tools that will use synchronized measurements to derive insight on the input-output properties of power system components. For improving adaptive control designs, efficient probing signals have been designed for online estimation of transfer functions. An open-source model identification toolbox has been developed for verifying and validating the dynamic performance of power system components using available synchrophasor measurements.

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1. Introduction

1.1 Background

Situational awareness is important for secure and reliable operation of power systems. This requires information about key performance indicators, so that alarms can be issued if these indicators are outside their acceptable limits for the operators to take appropriate measures to steer the power system into a safe secure state.

One of the many topics in the context of stable system operation in power systems is the concept of small-signal stability. This is characterized by the presence of well-damped system modes at the operating point in a linearized system model. For a traditional power system which includes aggregate positive sequence models of inverter-based resources (IBRs) such as solar and wind generation, the quasi-stationary dynamics can be represented by a differential-algebraic model of the form:

$$\begin{aligned} \dot{\boldsymbol{x}} &= \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y}) \\ 0 &= \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{y}) \end{aligned} \tag{1}$$

where, $\boldsymbol{x}$ is a vector of dynamic state variables such as rotor angles and rotor frequencies and $\boldsymbol{y}$ is a vector of algebraic power-flow variables such as the bus voltages and phase angles. And $\boldsymbol{g}$ represents the power flow equations. This simplified model reduces the computational complexity for analysis of the model. It has been found that to study small-signal stability in power system models, it is useful, when applicable, to reduce the non-linear DAE model in (1) to a linear one and use well developed tools from linear system theory to define and use key performance indicators to access the stability.

$$\begin{aligned} \dot{\boldsymbol{x}} &= \boldsymbol{A_d}\boldsymbol{x} + \boldsymbol{B_d}\boldsymbol{v} \\ 0 &= \boldsymbol{C_d}\boldsymbol{x} + \boldsymbol{D_d}\boldsymbol{v} \end{aligned} \tag{2}$$

Where, $\boldsymbol{A_d}, \boldsymbol{B_d}, \boldsymbol{C_d},$ and $\boldsymbol{D_d}$ are the Jacobian matrices found at a particular operating condition, say, $[\boldsymbol{x_o}, \boldsymbol{y_o}]$. The linear model is then used to analyze the modal properties in the system, which can manifest in the form of poorly damped oscillations if some of the complex conjugate eigenvalues are poorly damped. The linear model (2) is useful in context of control design, and a well-designed linear controller using this model can be effective for improving small-signal stability. This traditional model-based controller design, however, is being rendered difficult with the new developments in power systems.

Power grids around the world are steadily transitioning to sustainable renewable energy sources and storage devices, broadly denoted as inverter-based resources (IBR). The interaction of IBR devices with synchronous generators and their controls renders the dynamics of the emerging power grid to be complex and challenging. Wide-area oscillations ([1]-[4]) related to poorly damped inter-area system modes have been observed during many recent events in Europe. Novel adaptive control designs are needed for addressing these stability concerns. Traditional control designs based on offline system models are proving inadequate because simulated responses of the offline models do not accurately capture the dynamic responses of the power grids. There is an urgent need to develop new methods and tools which can effectively and realistically represent the input-output properties in IBR-rich power grids for adaptive control designs and for system monitoring.

Massive integration of inverter based distributed energy resources (DERs), specifically photovoltaic (PV) systems, is progressing at a rapid pace in power grids all over the world. This in turn is posing serious challenges to planning and operation of the power system, including on the reliability and stability of bulk power systems (BPS). The recent blue cut fire event in Southern California on Aug 16, 2016 [5] led to a loss of 1200 MW of transmission-connected PV generation in response to a routine transmission line fault. The recent NERC study on BPS disturbances that occurred in Southern California area on April and May 2018 [6] further highlights the continued concerns due to momentary cessation and tripping of both BPS-connected and distribution-connected PV systems during a transmission system fault. Initial studies indicate that the loss of PV generation during these events occurred even though the PVs were in apparent compliance with the ride-through and momentary cessation requirements. The NERC study concluded that the cause of PV system tripping included ac undervoltage, transient sub-cycle ac overvoltage, ac overcurrent, and dc reverse current during the fault. These events have highlighted the significance of understanding and modeling the protection algorithms and dynamic characteristics of PV resources, both at the transmission and distribution levels, to better represent the role of DERs in BPS simulation studies in power system planning and operation.

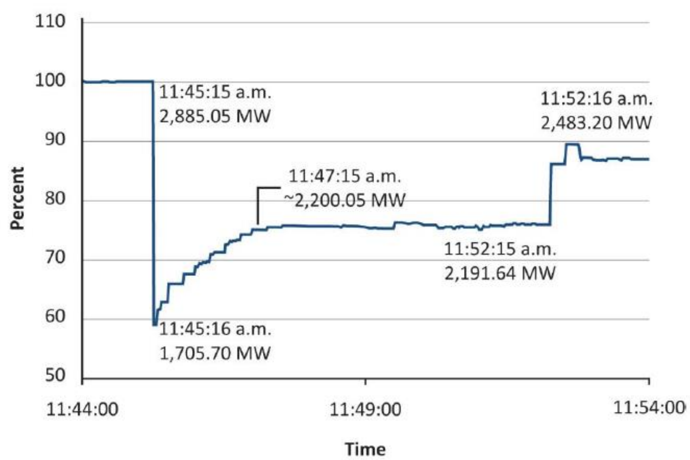

Figure 1. SCE Solar Resource Output SCADA Graph during 8/16/2016 event [5]

1.2 Overview of Problem

The modeling of the IBR devices is inherently challenging because of the following reasons: a) proprietary nature of internal controls which may not be fully disclosed by the vendors, b) rapid advances in the IBR technology that will lead to many different versions of IBR devices operating together in the power grid, and c) broad diversity of control designs among the millions of IBR devices in future power grids. Therefore, the traditional approach of developing detailed physical models of power system components for power system planning and control designs may not be practical for IBR-rich power systems. For managing and operating future power grids, we need to

develop novel adaptive modeling formulations where the input-output dynamic properties of the IBR devices are adequately described using standard functional models for studying their impact on the bulk power system. Accordingly, the focus in this project is on the development of three measurement-based system identification methodologies which address different aspects of online system identification in IBR-rich bulk power systems.
The three methodologies are namely: a) System identification strategies for online model estimation (Chapter 2), b) Observability analysis of standard IBR models (Chapter 3), and c) Open-source model validation toolbox (Chapter 4).

1.3 Technical Overview

The project research included three tasks:

1) <u>System identification strategies for online model estimation:</u>

With the increased presence of intermittent energy sources and with the threat of unpredictable extreme weather events and cyber threats, the operating conditions of future power systems are expected to change suddenly and rapidly. Therefore, traditional control designs based on offline system models may become too conservative and too difficult to maintain in keeping up with such system changes. In this project, we have developed a system identification strategy for online estimation of system models as needed for adaptive control designs. This includes the use of a suitable probing signal for quickly and accurately estimating the input-output properties for specific controllers such as HVDC modulation schemes. A chirp signal is synthesized to be used as excitation for the probing test.

2) <u>Observability analysis of IBR models:</u>

Owing to the proprietary nature of internal switching mechanisms and controls, it may be very difficult to get detailed physical models of IBR devices. Moreover, the very large number of such devices in bulk power systems may also make it impractical to model each IBR device in detailed representation. From bulk power system perspective, it is important to capture the relevant aggregate dynamic response of a group of IBR devices such as in wind farms, solar plants, and at the feeder level in distribution networks. In this context, a fundamental question arises as to what linear and nonlinear features of IBR device models are significant in influencing the bulk power system response, and whether those features can be estimated using external measurements. In this project, we have studied the importance and observability of the critical internal features of IBR devices by focusing on a subset of standard IBR models in consultation with RTE. The availability of relevant IBR models has been a challenge and we focused on setting up suitable IBR-rich test cases for future studies.

3) <u>Open-source toolbox for model validation:</u>

PI's research group at WSU had proposed the concept of system model validation [7] and power plant model validation [8] twenty years ago, and these concepts have become standard industry practices now. There are several commercial model validation packages available today, and each is tied to a specific transient stability simulation package and its vendor. Each of these tools has its own limitations in the form of formulations, user friendliness, and choice of optimization methods. In this task, we have developed an open-source model validation toolbox that was custom developed in collaboration with RTE for providing a common user platform for the industry. The tool provides metrics for comparing whether the simulated model response matches well with system response from archived measurement data, and for improving/tuning the parameters to improve the models as needed. Archived synchrophasor measurements and other types of synchronized high-speed measurements such as from Digital Fault Recorders (DFRs) can be used for the model verification and validation. The methodology can also be tested by using emulated measurements such as from three-phase EMTP type simulations that can be used to validate positive sequence type models used in transient stability studies.

1.4 Discussion

1.4.1 Potential Benefits

The proposed research will address an important operational reliability concern related to designing and operating stability controls in IBR-rich modern power grids. The research if successful will help the industrial partner on the project, RTE France, to address stability monitoring and operational concerns in the RTE system. In a broader sense, the formulations and methodology developed in the project will benefit the entire PSERC community by improving the understanding of IBR device related issues in the power grid.

1.4.2 Outcomes

The following outcomes serve as deliverables:

1) Study on effective probing signal use and online system identification methodologies for characterizing the input-output properties online using synchronized measurements.
2) Two test systems in PSCAD for analyzing the interaction of IBRs in a power system and for studying the aggregated effect of large number of IBRs from bulk power system perspective.
3) An open-source platform and toolbox for validation and estimation of standard model features using synchronized measurements.

1.4.3 Potential Applications:

The project is strongly motivated by the practical needs of the project sponsor RTE and as such, the WSU project team worked closely with RTE engineers in representing the system needs and modeling formulations of the RTE power system using RTE PMU data. The probing signal designs are intended to be tested on HVDC modulation controllers operated by RTE, while the IBR models and model validation framework will be targeted towards standard models in use at RTE.

1.4.4 Related Work:

There is limited research activity on the general topic of online system identification methods both in academia and in industry. There is some earlier work over ten years ago on probing signal design for the Pacific DC Intertie (PDCI) HVDC lines in Pacific Northwest. There is little earlier theoretical work related to Task 2 on theoretical study of observable nonlinear features of IBR dynamics. On Task 3, there has been an extensive set of papers, methods, and tools proposed.

1.4.5 How this Work Differs from Related Work:

In Task 1, our work designed probing signal and accessed use of system identification methods for the needs of RTE. Task 2 addresses a new theoretical question on what internal features of IBR models can be observed and estimated using external measurements. In Task 3, this project proposes to integrate the open-source transient stability framework being developed at RTE into a new open-source model validation toolbox that would benefit PSERC and the broader community.

Relationship of this Work to the Research Plan and Topic Areas for this Solicitation: This project is directly supported in its entirety by a PSERC industry member, RTE, to support their needs in stability control design and model validation studies of the RTE power system. In a broad sense, the research addresses system identification, and its impact in the systems stem of PSERC.

1.5 Report Organization

The report is organized as follows. Each task from tasks 1, 2 and 3 will be discussed in sections 2, 3 and 4 respectively. Each section will introduce problem statements along with literature review, theoretical background, and a summary of project results. Test results will also be presented followed by discussions and concluding remarks.

2. Task 1: System identification strategies for online model estimation

2.1 Introduction and Problem Statement

Online input output model estimation and adaptive control in power systems has already been emphasized in section 1 of the report. We shall briefly cover literature review on this topic and summarize the existing knowledge in this area. There are two ways to estimate the input output properties of a system in an online scheme, viz.: (1) Using ambient phasor measurement units (PMU) data, which refers to the process noise of system, characterized by ambient load fluctuations that constantly excite the system [9]. (2) Using probing signal to excite system dynamics and recording and analyzing the response. Both these methods have their own strengths and weaknesses.

Ambient data-based system identification requires measurements from large loads that have good controllability against the modes of interest. An advantage of ambient data-based estimation is that we do not need to inject any power into the system, thus it is a noninvasive, passive way of getting the required information. Moreover, since ambient data is always available this type of identification maybe run at any time and consequently be used to update the controller. A downside of this is that, since the information content in each load fluctuation is small, tools designed to extract dynamics information usually require a lot of data, typically around five minutes of data. Moreover, due to longer data windows required, the system is prone to change in between, leading to compromised performance of the subsequently designed controller. Error margins associated with ambient data-based estimations and controls are also larger compared to the probing-based methods. Probing tests pose an advantage there in that they have a larger signal-to-noise ratio, thus reducing error in estimation and control. They can be implemented in an efficient way, by designing custom probing signals, for improved and faster performance. These nonetheless pose a stress on the system, which may lead a weakly stable system into instability. These also require specialized setups in desirable locations to inject power into the system.

Although probing has been in use in power system dynamic response estimation for quite some time now, not much work has been done on probing signal design. Researchers in [10]-[12] have proposed a multi-sine signal for probing and designed by minimizing the estimation error against the constraints of system disturbance and signal energy. The problem is formulated in the frequency domain. There is no well-known example of these custom designed signals being used in real applications yet.

In this project, we have worked with a custom designed probing signal (linear chirp signal) to excite system dynamics, from a feasible location, in an online setting. The PMU data is then used to read the response of system against the excitation. Analysis is then performed on this data to access input output properties of power system. The analysis has been performed on two-area Kundur system and WECC 240-bus system from NASPI Contest Cases (2021). Subspace identification (SSI), Fast Fourier Transform (FFT), Fast Synchro-Squeezing Transform (FSST) and Frequency Domain Least Squares (FDLS), a method developed by WSU Pullman [9], have been compared for estimation of system input output properties.

In the following, a brief discussion on the theoretical background of the tools used in this project will be presented, viz: Linear chirp signal and the identification methods.

2.2 Theoretical Background

2.2.1 Chirp Signal

A chirp signal is a signal whose frequency changes with time. Depending how the frequency varies with time, a few of the chirp signals that have been proposed in knowledge are:

1. Linear chirp
2. Exponential chirp
3. Up-Down modulated chirp
4. Sine wave modulated chirp
5. Bird chirp

Linear and exponential chirp signal is demonstrated in figures 1 and 2.

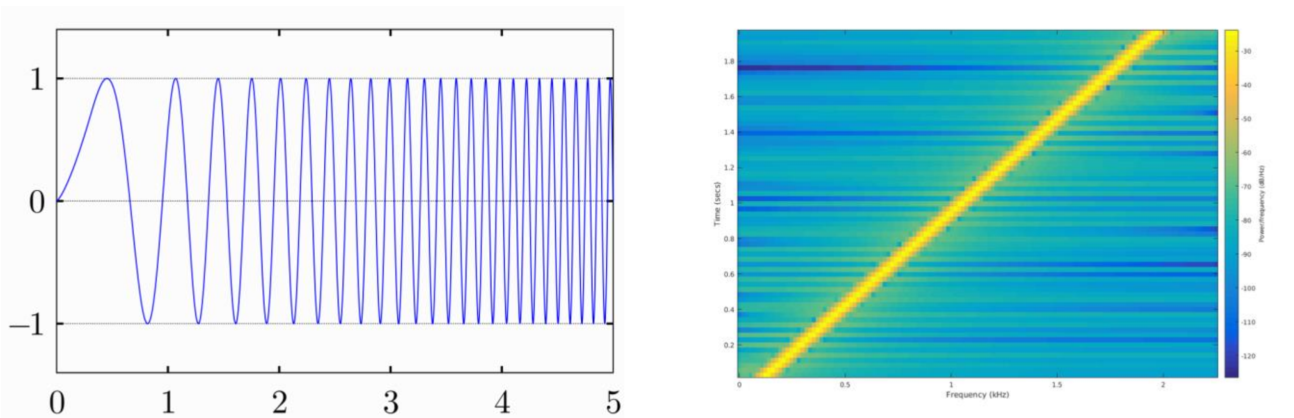

Figure 1: (left) A linear chirp waveform; a sinusoidal wave that increases in frequency linearly over time [13], (right) Spectrogram of a linear chirp. The spectrogram plot demonstrates the linear rate of change in frequency as a function of time, in this case from 0 to 7 kHz, repeating every 2.3 seconds. The intensity of the plot is proportional to the energy content in the signal at the indicated frequency and time [14].

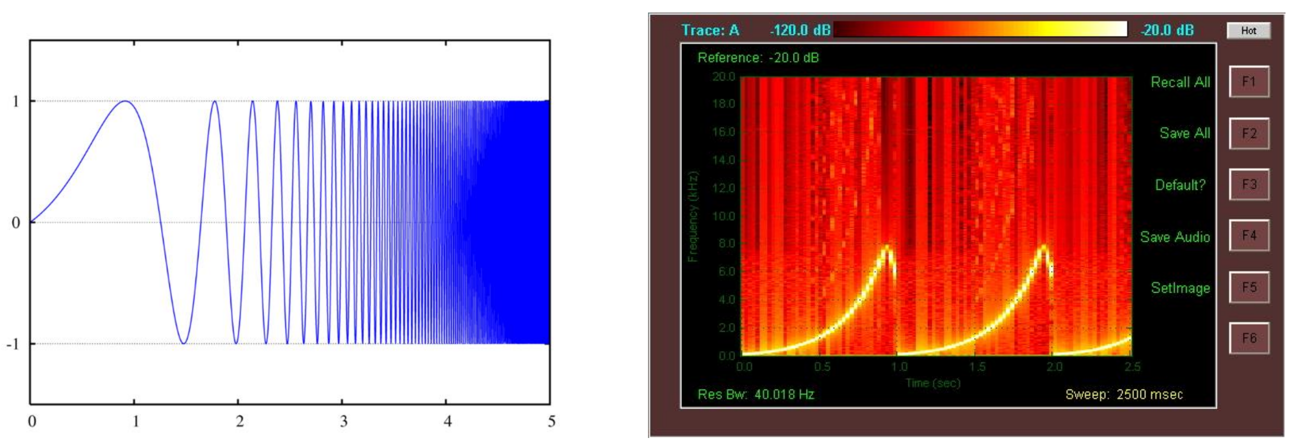

Figure 2: (left) A exponential chirp waveform; a sinusoidal wave that increases in frequency linearly over time [15], (right) Spectrogram of an exponential chirp. The exponential rate of change of frequency is shown as a function of time, in this case from nearly 0 up to 8 kHz repeating every second. Also visible in this spectrogram is a frequency fallback to 6 kHz after peaking, likely an artifact of the specific method employed to generate the waveform [16].

For this project, RTE France (the sponsor of project) has designed a linear chip signal, the detail of which is provided in section 2.3.

2.2.2 Subspace Identification (SSI)

In a linear dynamic system defined as:

$$\begin{aligned}\dot{\boldsymbol{x}} &= \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \\ \boldsymbol{y} &= \boldsymbol{C}\boldsymbol{x} + \boldsymbol{D}\boldsymbol{u}\end{aligned} \tag{3}$$

If we have the information of the inputs and outputs, i.e., $\boldsymbol{u}$ and $\boldsymbol{y}$, the problem of finding a state space representation, $\widehat{\boldsymbol{A}}, \widehat{\boldsymbol{B}}, \widehat{\boldsymbol{C}}$ &$\widehat{\boldsymbol{D}}$; such that:

$$\begin{aligned}\dot{\boldsymbol{x}} &= \widehat{\boldsymbol{A}}\boldsymbol{x} + \widehat{\boldsymbol{B}}\boldsymbol{u} \\ \boldsymbol{y} &= \widehat{\boldsymbol{C}}\boldsymbol{x} + \widehat{\boldsymbol{D}}\boldsymbol{u}\end{aligned} \tag{4}$$

Is referred to as subspace identification. Since the subspace model of a dynamical system is not unique, what we get as a product of SSI, is the representation of original system in another basis. For many applications, usually a reduced state model is desirable to be identified instead of a full order model, thus the name subspace identification. This goes together with the notion that the response of a linear system in a particular frequency range is mostly defined by dominant eigen values (while the others may correspond to system and measurement noise), thus wasting computational resources on estimating a full-scale model is usually undesirable. As an example, a full-scale input-output model of power system may contain thousands of states, but it is usually well approximated by one to five pair of eigen values in a small enough frequency range, depending on application. SSI will only be covered here briefly. Interested readers are encouraged to explore the book, Subspace identification for linear systems, by Peter Van Overschee [17]. Most SSI tools work in a three-step algorithm:

1. Form block Hankel matrices using input-output data.
2. Find state sequency matrix $\boldsymbol{X_k}$, using block Hankel matrices, and reduce it to desired order.
3. Use least squares fit to find $\widehat{\boldsymbol{A}}, \widehat{\boldsymbol{B}}, \widehat{\boldsymbol{C}}$ &$\widehat{\boldsymbol{D}}$ from:

$$\begin{bmatrix}\boldsymbol{X_{k+1}} \\ \boldsymbol{Y_k}\end{bmatrix} = \begin{bmatrix}\widehat{\boldsymbol{A}} & \widehat{\boldsymbol{B}} \\ \widehat{\boldsymbol{B}} & \widehat{\boldsymbol{C}}\end{bmatrix}\begin{pmatrix}\boldsymbol{X_k} \\ \boldsymbol{U_k}\end{pmatrix} \tag{5}$$

An error covariance matrix may also be estimated. We use a robust combined algorithm from chapter 4 of [17], as shown in figure 3. Different implementations of stochastic SSI may be performed using the weight matrices as shown in figure 4. We shall use n4sid for our purposes. SSI methods are very good at decomposing the system response against individual eigen values, pose minimum bias in presence of a disturbance and exhibit strong rejection of noise. These features make them useful for practical applications. SSI methods are however computationally inefficient and may or may not be suitable for real time applications depending on the size of the problem. Fort the purpose of this project, SSI method is deemed useful because of the small size of the problem.

Robust combined algorithm:

1. Calculate the oblique and orthogonal projections:

$$\mathcal{O}_i = Y_f /_{U_f} \boldsymbol{W}_p \quad , \quad \mathcal{Z}_i = Y_f / \begin{pmatrix} \boldsymbol{W}_p \\ \boldsymbol{U}_f \end{pmatrix} \quad , \quad \mathcal{Z}_{i+1} = Y_f^- / \begin{pmatrix} \boldsymbol{W}_p^+ \\ \boldsymbol{U}_f^- \end{pmatrix} .$$

2. Calculate the **SVD** of the weighted oblique projection:

$$\mathcal{O}_i \Pi_{U_f^\perp} = U S V^T .$$

3. Determine the order by inspecting the singular values in S and partition the **SVD** accordingly to obtain U_1 and S_1.

4. Determine Γ_i and Γ_{i-1} as:

$$\Gamma_i = U_1 S_1^{1/2} \quad , \quad \Gamma_{i-1} = \underline{\Gamma_i} .$$

5. Solve the set of linear equations for A and C:

$$\left(\begin{array}{c} \Gamma_{i-1}^\dagger . \mathcal{Z}_{i+1} \\ \hline Y_{i|i} \end{array} \right) = \left(\begin{array}{c} A \\ \hline C \end{array} \right) . \Gamma_i^\dagger . \mathcal{Z}_i + \mathcal{K} . U_f + \left(\begin{array}{c} \rho_w \\ \hline \rho_v \end{array} \right) .$$

   Recompute Γ_i and Γ_{i-1} from A and C.

6. Solve B and D from:

$$B, D = \arg \min_{B,D} \| \begin{pmatrix} \Gamma_{i-1}^\dagger . \mathcal{Z}_{i+1} \\ Y_{i|i} \end{pmatrix} - \begin{pmatrix} A \\ C \end{pmatrix} . \Gamma_i^\dagger . \mathcal{Z}_i - \mathcal{K}(B, D) . U_f \|_F^2 .$$

7. Finally, determine the covariance matrices Q, S and R as:

$$\begin{pmatrix} Q & S \\ S^T & R \end{pmatrix} = \mathbf{E_j} [\begin{pmatrix} \rho_w \\ \rho_v \end{pmatrix} . \begin{pmatrix} \rho_w^T & \rho_v^T \end{pmatrix}] .$$

Figure 3: A schematic overview of a robust deterministic stochastic identification algorithm. [17]

	W_1	W_2
N4SID	I_{li}	I_j
MOESP	I_{li}	$\Pi_{U_f^\perp}$
CVA	$\Phi_{[Y_f/U_f^\perp, Y_f/U_f^\perp]}^{-1/2}$	$\Pi_{U_f^\perp}$

Figure 4: Overview of the special choices of W1 and W2 to obtain the published algorithms N4SID, MOESP and CVA. [17]

2.2.3 Fast Fourier Transform (FFT)

Fast Fourier transform (FFT), projects the time signal onto orthogonal eigen functions, sines, and cosines to obtain a frequency domain representation of the time signal.

$$\hat{f}(\eta) = \int_{\mathbb{R}} f(x) e^{-2j\pi\eta x} dx \tag{6}$$

Since convolution in time domain is a product in frequency domain, an estimate of the frequency response of the linear system may be obtained by taking the ratio of FFT of output to FFT of input. Frequency bin size may be customized to obtain a clean result.

$$G_{rm}(\omega) = {FFT(m_r)}\big/{FFT(m_m)} \tag{7}$$

FFT is expected to produce good amplitude estimates with reasonable signal-to-noise ratio (SNR), however it is expected to struggle with phase response estimates in the SNR ranges where SSI methods perform well enough. This will be demonstrated in section 2.4.

2.2.4 Fast Synchro-Squeezing Transform (FSST)

Short window Fourier transform (SFFT) is a running window Fourier transform that produces the system instantaneous frequency response as function of time. This is done by including a window function in the definition of FFT (6) like:

$$\begin{aligned} V_f^g(t,\eta) &= \int_{\mathbb{R}} f(u) g(u-t) e^{-2j\pi\eta(u-t)} du \\ \hat{\omega}_f(t,\eta) &= \frac{1}{2\pi}\partial_t \arg(V_f^g(t,\eta)) = \eta + \operatorname{Im}\left\{ \frac{V_f^{g'}(t,\eta)}{2\pi V_f^g(t,\eta)} \right\} \end{aligned} \tag{8}$$

Fast Synchro-Squeezing Transform (FSST) is obtained by squeezing SFFT around dominant frequencies under the assumption of slow amplitude variation [18],[19]. Like FFT, FSST can also be used to estimate frequency response of the system but as a function of time. For a time-invariant system, this may be compressed along time dimension to obtain the total system frequency response.

$$G_{rm}(\omega) = {FSST(m_r)}\big/{FSST(m_m)} \tag{9}$$

Like FFT, FSST is also expected to pose a poor phase response estimation under moderately low SNR, which renders to useless with real data. This will be demonstrated in section 2.4.

2.2.5 Output Error Method (OE) [MATLAB]

We have also included MATLAB's OE in our analysis. It is close to Auto Regressive Moving Average methods with exogenous inputs (ARMAX), in that it uses a polynomial fit mechanism. The method assumes a general output-error model structure like:

$$y(t) = \frac{B(q)}{F(q)} u(t - n_k + e(t)) \tag{10}$$

The orders of output error methods are:

$$\begin{aligned} nb: B(q) &= b_1 + b_2 q^{-1} + \cdots + b_{nb} q^{-nb+1} \\ nf: F(q) &= 1 + f_1 q^{-1} + \cdots + f_{nf} q^{-nf} \end{aligned} \tag{11}$$

OE methods have poor performance under poor SNR, and these are very order sensitive. Not suitable for the application in question.

2.2.6 Frequency Domain Least Squares (FDLS)

Recent paper [9] developed a novel method for the estimation of input-output frequency response of power system using ambient load fluctuation data and PMU data from wide area measurements. The method is an input-output method and is explored with the probing signal in this project. We'll briefly discuss the summary of this method here:

Consider a second order dynamical system, characterized in complex frequency domain by:

$$\mathrm{H}_{\mathrm{i,\,m}}(\mathrm{s}) = \frac{\mathrm{d}_{\mathrm{i,\,m}}\mathrm{s}^2 + \alpha_{\mathrm{i,\,m}}\mathrm{s} + \beta_{\mathrm{i,\,m}}}{\mathrm{s}^2 + \sigma \mathrm{s} + \Omega} \tag{12}$$

Cross multiplying and rearranging at s=jω:

$$\begin{gathered} (\mathrm{j}\omega \mathrm{Y_i})\sigma + (\mathrm{Y_i})\Omega - \sum_{\mathrm{m}=1}^{\mathrm{M}} (\mathrm{j}\omega \mathrm{U_m})\alpha_{\mathrm{i,\,m}} - \sum_{\mathrm{m}=1}^{\mathrm{M}} (\mathrm{U_m})\beta_{\mathrm{i,\,m}} + \sum_{\mathrm{m}=1}^{\mathrm{M}} (\omega^2 \mathrm{U_m})\,\mathrm{d}_{\mathrm{i,\,m}} = \mathrm{Y}_i \omega^2 \\ \text{1.} \quad \text{with } \ \mathrm{i} = 1,2,\ldots,\mathrm{N} \quad \& \quad \omega_1 < \omega < \omega_2 \end{gathered} \tag{13}$$

(13) represents a least squares problem, with input-output data (frequency domain) as the knowns and the coefficients from (12) as the unknowns. The method can likewise be extended to higher order formulation. Interested readers are encouraged to check out the publication [9]. This method has a good performance in small frequency ranges, and the performance is a better function of SNR than all previous mentioned methods. The method is also faster than SSI methods, it however struggles with smaller data windows, high order estimation and longer frequency ranges.

2.3 Proposed Solution

We have explored custom probing signal-based system identification in power systems in this project, with the goal of designing a field test using the findings of research. The signal that RTE France has designed is a linear chirp signal that spans a small range of frequency [0.1~1] Hz, with an amplitude range of [10-100] MW for simulation, and 4 mins in duration. Subject to approvals, the plan is to inject the probing signal into the controller of French side HVDC terminal of the HVDC line between France and Spain. System response will then be recorded using PMU data. Single input multiple output (SIMO) frequency response will be estimated between HVDC terminal and designated measurement points in power system. Consequently, a robust adaptive damping controller will be designed using estimated frequency response (Not a part of this project).

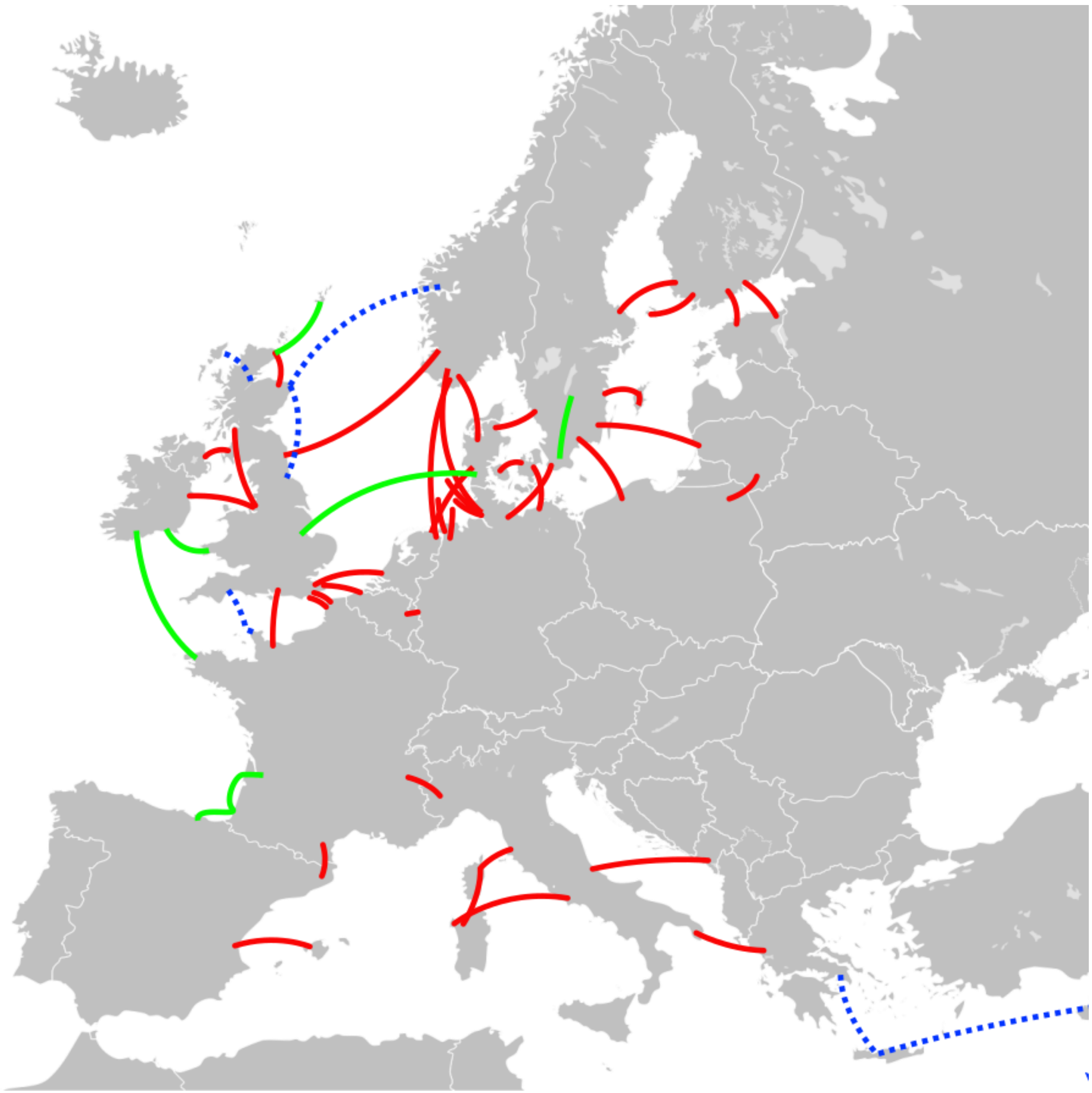

Figure 5: HVDC connections around Europe, ●red are existing, ● blue is proposed, ● green are approved. Image source [21]

2.4 Simulation and Results

In this section, we will be using the 2-area-11-bus-4-machine Kundur system to illustrate probing-based-system identification. An HVDC line is connected between bus 7 and bus 9 to mimic the one connected between France and Spain in European grid. The one-line diagram of the system is shown below, where the line resistance and reactance and the shunt capacitor at bus 7 and 9 can be found in [22].

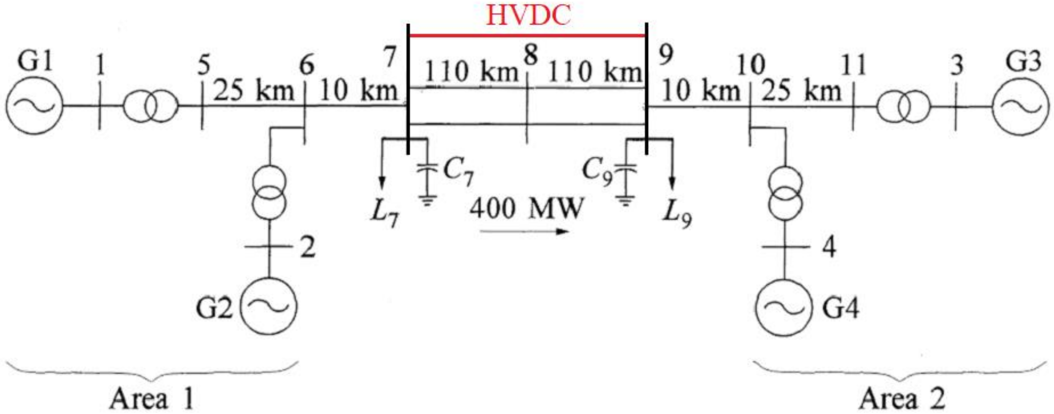

Figure 6. One-line diagram of the Kundur test system [22]

In this system, we have represented the generators with two-axis flux decay machine models each equipped with a single state exciter, a single state governor and power system stabilizer. In general, power system dynamics is modeled by differential equations describing the system dynamics along with a set of algebraic equations defined by the system power flow solutions [22]. The equations describing generator models are follows:

$$\begin{gathered} V_{di} = V_i \cos\left(\delta_i - \Phi_i\right) \\ V_{qi} = V_i \sin\left(\delta_i - \Phi_i\right) \end{gathered} \tag{14}$$

$$\begin{cases} T'_{di}\dot{E}'_{qi} = -E'_{qi} - (X_{di} - X'_{di})I_{di} + E_{fdi} \\ T'_{qi}\dot{E}'_{di} = -E'_{di} + \left(X_{qi} - X'_{qi}\right)I_{qi} \\ \dot{\delta}_i = \omega_i - \omega_s \\ 2H_i\dot{\omega}_i = P_{mi} - \left(E'_{qi}I_{qi} + E'_{di}I_{di}\right) - D_i(\omega_i - \omega_s) \end{cases} \tag{15}$$

where $\omega_s = 120\pi$, $I_{di} = \frac{E'_{qi} - V_{qi}}{X'_{di}}$, $I_{qi} = -\frac{E'_{di} - V_{di}}{X'_{qi}}$. The exciter equations are as follows:

$$T_{Ai}\dot{E}_{fdi} = -E_{fdi} + K_{Ai}(V_{refi} - V_i) \tag{16}$$

The governor equations are:

$$T_{sgi}\dot{P}_{mi} = -P_{mi} + K_{sgi}(P_{ref} - \frac{1}{R_i}(\omega_i - \omega_s)) \tag{17}$$

Power system stabilizers are modelled as follows:

$$\begin{gathered} T_{wi}\dot{E}_{w1i} = -E_{wi} + T_{wi}\dot{E}_{2i} \\ T_{4i}\dot{E}_{2i} = -E_{4i} + E_{1i} + T_{3i}\dot{E}_{1i} \end{gathered} \tag{18}$$

$$T_{2i}\dot{E}_{1i} = -E_{1i} + E_{fdi} + T_{2i}\dot{E}_{fdi}$$

In the above equations, the subscript $i = 1, \ldots, 4$ denotes each of the four generators. HVDC connected between buses i and j is modelled like:

$$\begin{aligned} T_{Pi}\dot{E}_{Pi} &= -E_{Pi} + K_{Pi}\Delta\delta_{ij} \\ T_{Qwi}\dot{E}_{Qwi} &= -E_{Qwi} + T_{Qwi}\dot{\omega}_i \\ T_{Qi}\dot{E}_{Qi} &= -E_{Qi} + K_{Qi}E_{Qwi} \end{aligned} \tag{19}$$

Loads at bus 7 and 9 are modelled by 1% gaussian white noise. The system parameters are set such that we have a 2.5% damping at 0.6Hz inter-area mode. A probing signal is injected into the HVDC controller. Bus angle values are read from the PMU data and system identification is performed. Figure 7 presents results of SSI (N4SID) against that obtained from linearized system response. Calculations are done using MATLAB.

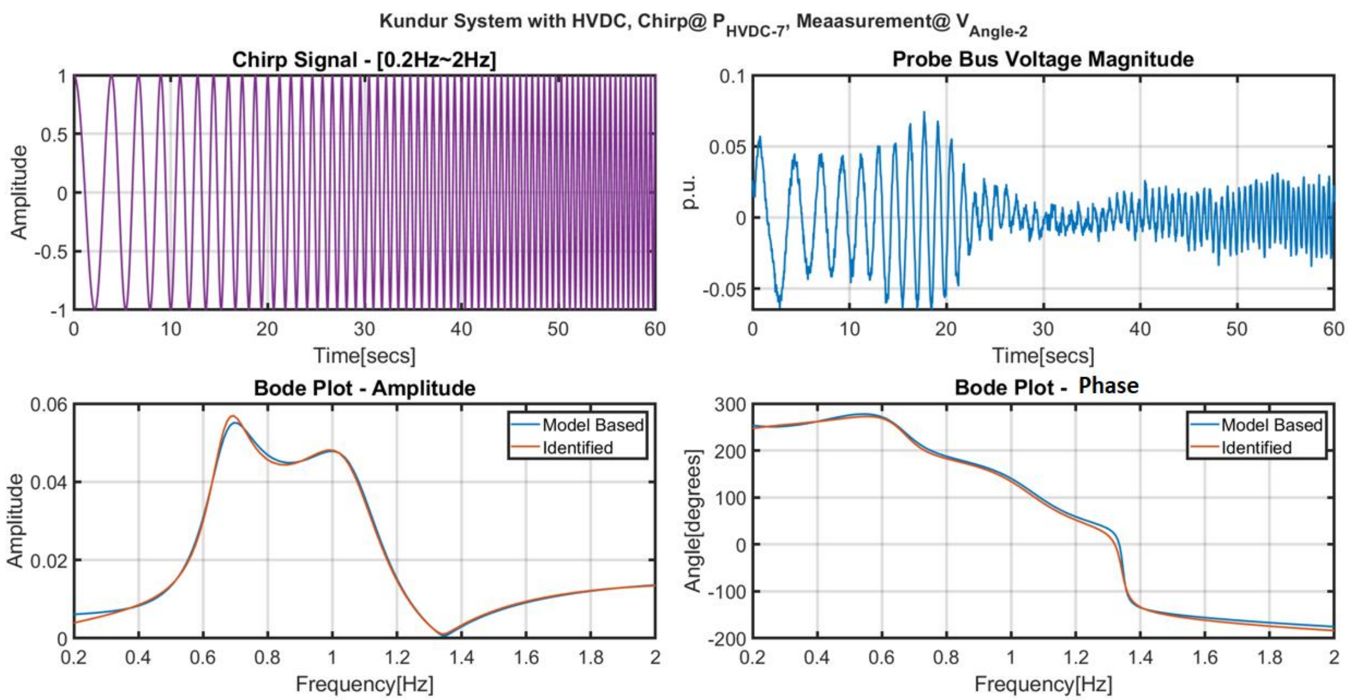

Figure 7: Results of SSI from Kundur System against a chirp excitation in real power on HVDC terminal connected at bus 7.

It is evident that SSI performed with probing signal, yields accurate system response, and maybe used in real systems for analysis. We have also tested this method in WECC 240-bus system, designed by NASPI for the FO source location contest shown in Figure 8. In this system, an HVDC line is connected between the bus 4010 and bus 2619. We have used the same dynamic models for HVDC here that we used for Kundur system. Loads are modelled with a 0.26% white gaussian noise. For the purposes of this report, two cases are considered: (1) No measurement noise, (2) 0.25% white gaussian measurement noise. A linear chirp signal is constructed using the UDM Editor as shown in Figure 9. The probing signal is injected into P-control of HVDC connected between buses 4010 and 2619 at bus 4010. A SISO system identification is performed using the probing signal (Chirp) as an input and real power of generators at bus 1431G as an output. Estimations with other measurements have comparative performance but have not been shared to save space. Simulations are done using DSA Tools package from Power Tech Canada [23].

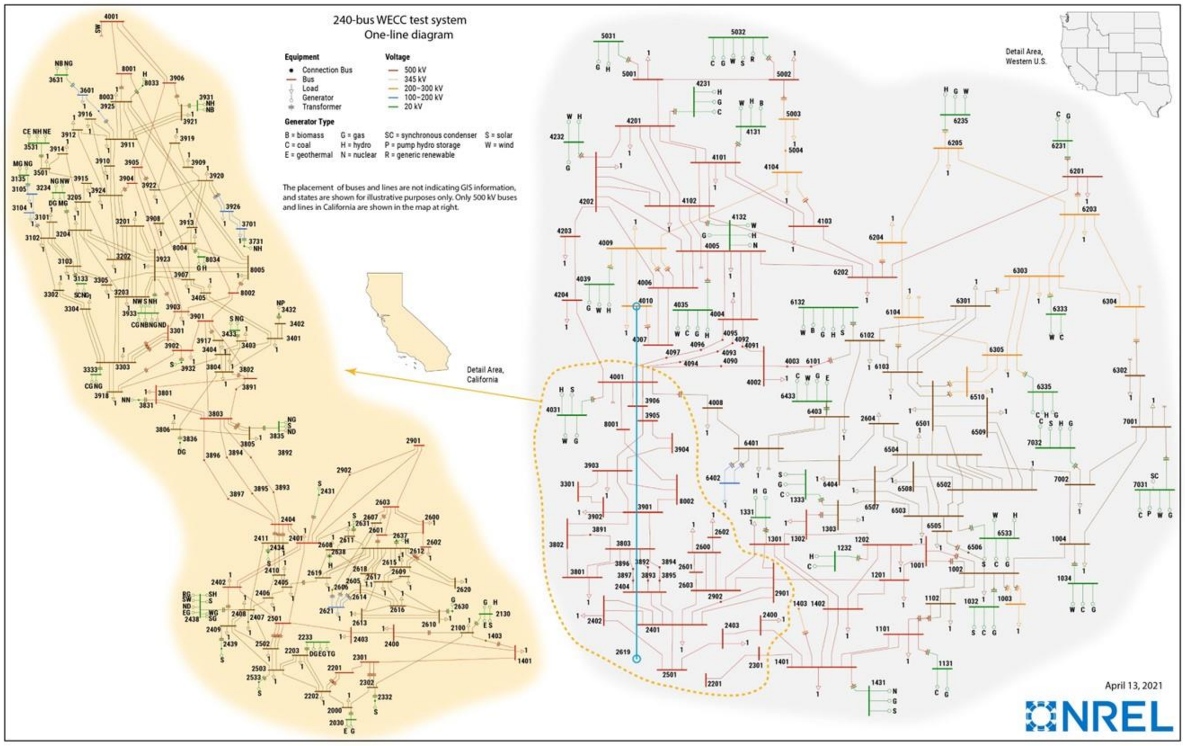

Figure 8: Mini WECC/WECC 240-bus system developed by NREL for NASPI FO Source Location Contest in 2021

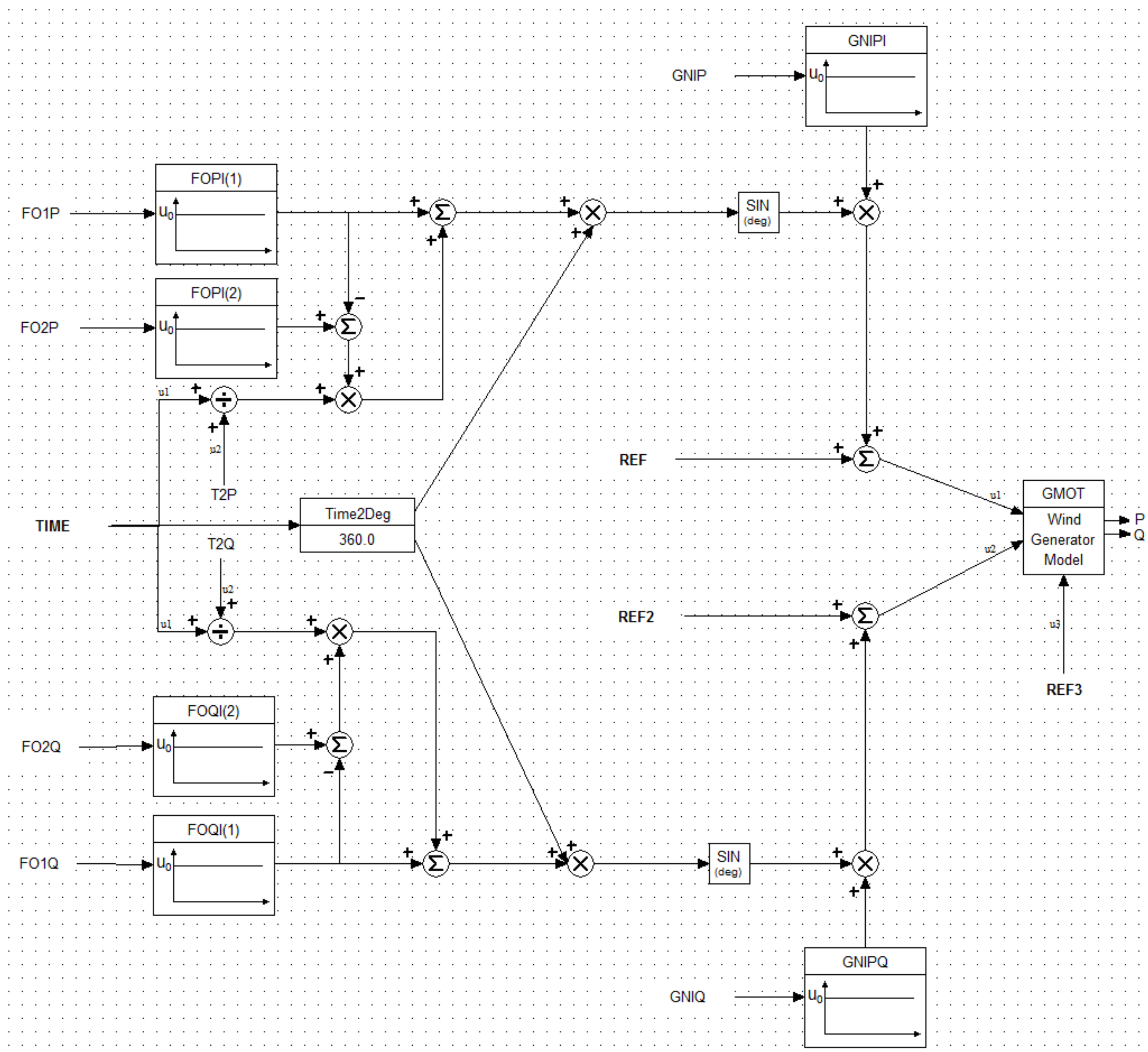

Figure 9: User defined module for linear chirp signal injection in HVDC model

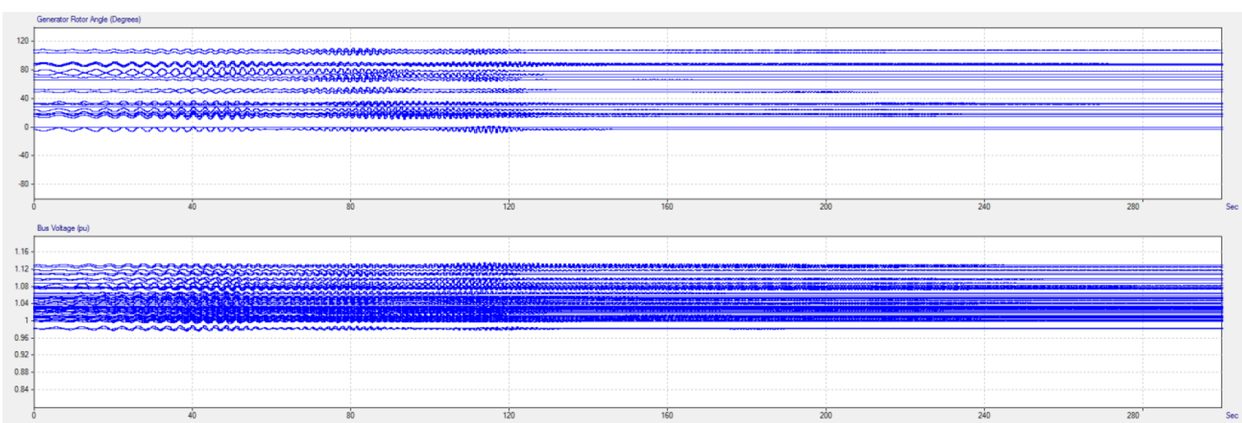

Figure 10: System response to chirp excitation (DSA Tools by Power Tech, Canada)

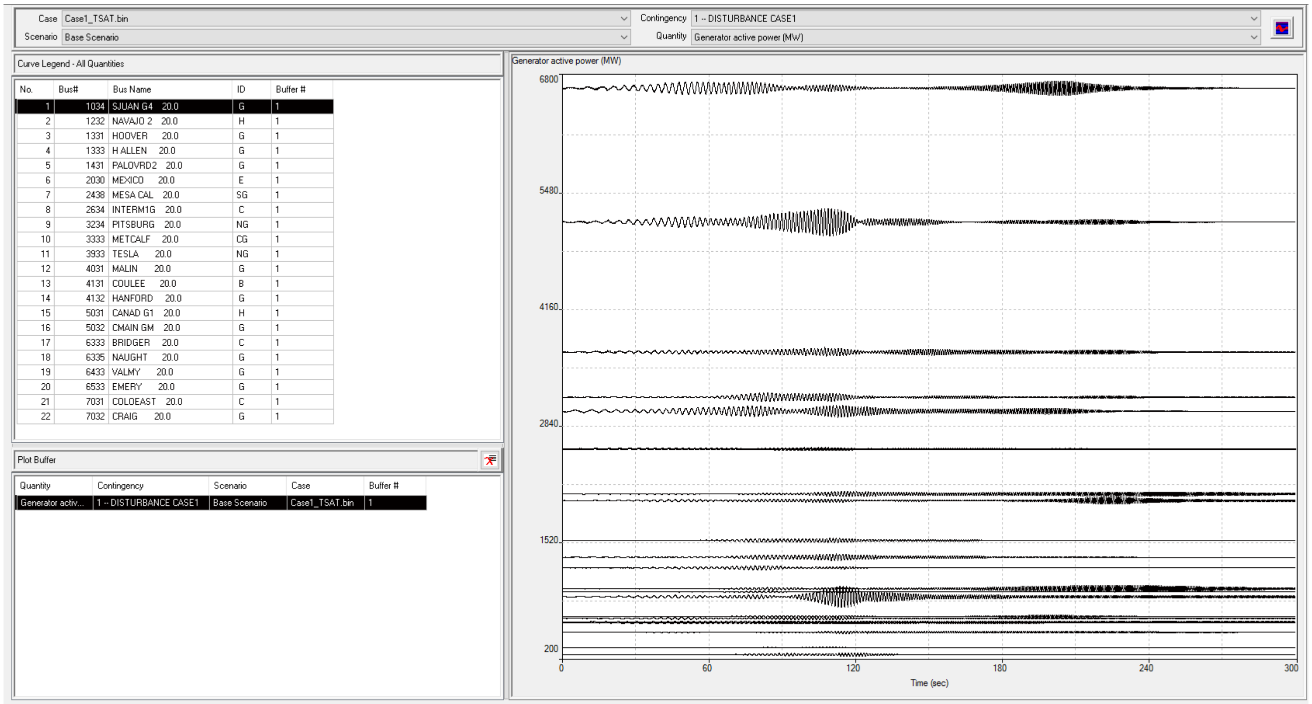

Figure 11: System Response to Chirp Excitation

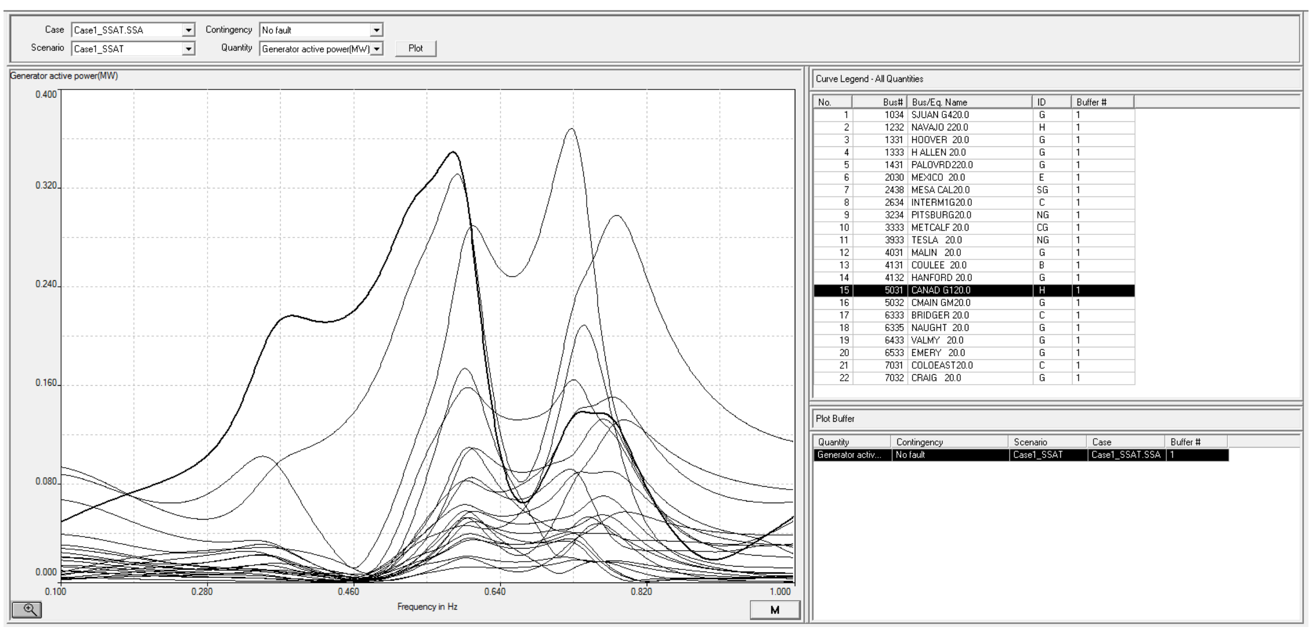

Figure 12: Frequency response between designated input and designated outputs. Computed using SSAT [23]

The system is excited using the custom linear chirp signal. The responses are read and used to estimate frequency response between designated inputs and outputs. Estimates are then compared with those obtained from the linearized model (SSAT). Results are shown in Figure 10-14.

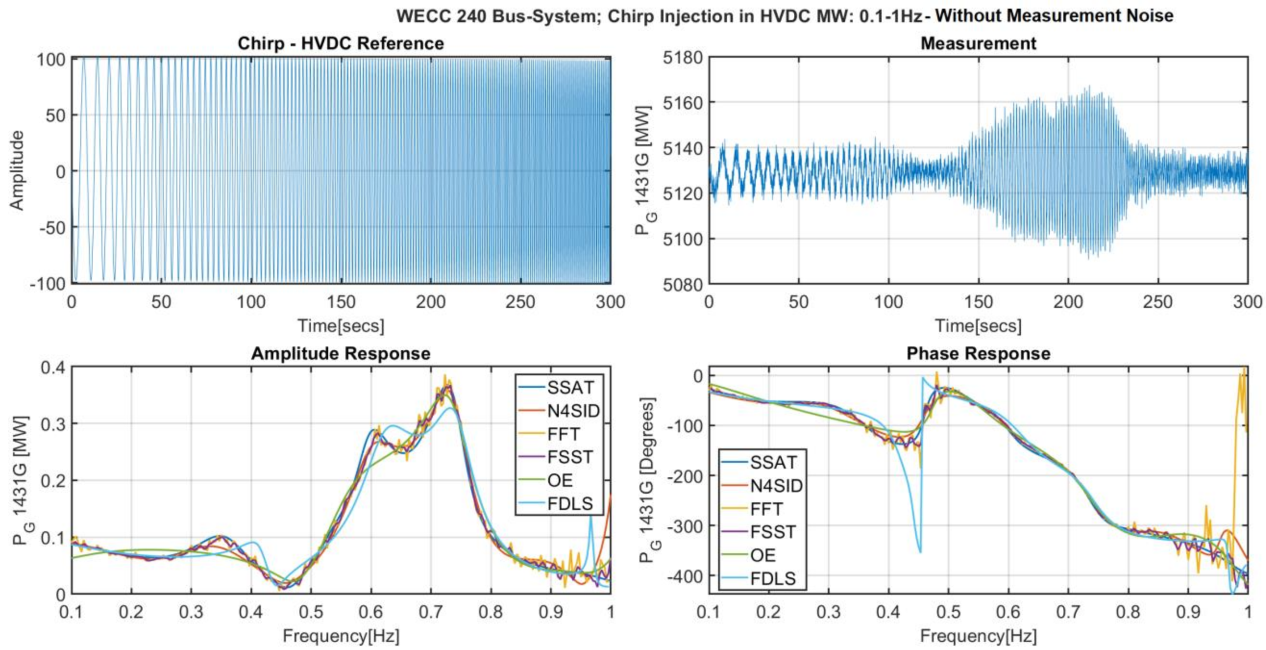

Figure 13: SSI results in WECC 240-bus system against different methods.

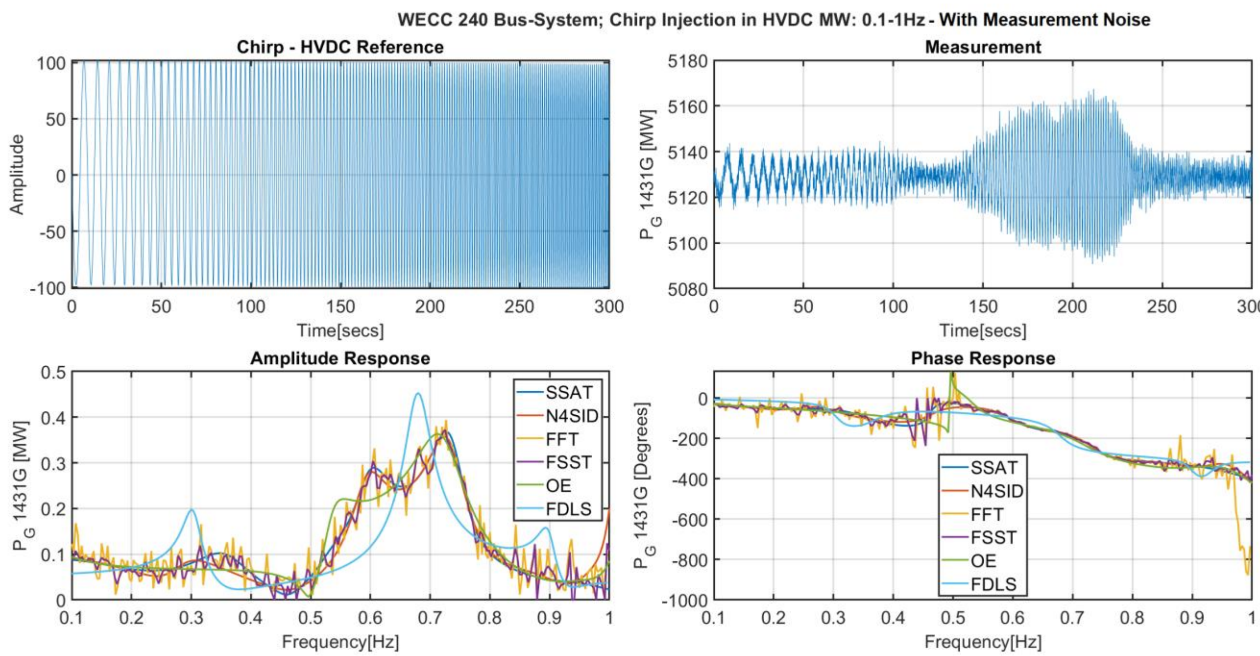

Figure 14: Depiction of poor performance of frequency domain methods for phase response estimation.

From the results in Figure 13, it appears that all methods have comparative performance in absence of measurement noise and a good signal to process noise ratio. But we see in Figure 14 that N4SID stands out in the presence of measurement noise. This is shown using MATLAB's 'GoodnessOfFit' in Table 1 below.

Table 1: Comparison of errors from different system identification methods

Method	**Error (Normalized RMSE* w.r.t. SSAT Results)**	
	Without Measurement Noise	With Measurement Noise
N4SID	4.3	3.8
FFT	10.1	15.4
FSST	2.8	13.6
OE	3.4	8.7
FDLS	17.4	8.1

* Root mean squared error

2.5 Discussion

In this section, we have shown that a custom designed linear chirp signal can be useful to excite system dynamics in the frequency range of interest and maybe used with system identification techniques to efficiently estimate the frequency response of system between designated inputs and designated outputs. Different system identification methods have been tested. It has been found that FFT and FSST have poor performance against phase response estimation in medium to low SNR range. Subspace identification and FDLS have good performance against poor SNR conditions. The proposed scheme and methods need to be tested on detailed models of real power systems.

3. Task 2: Observability Analysis of Inverter Based Resources

3.1 Introduction and Problem Statement

Many unprecedented events have been observed with the recent trend of massive integration of inverter-based resources (IBRs) in power systems. The large-scale integration of IBRs has resulted in interactions of significant influence between these resources among each other and with the synchronous generators and their controls present in the power system. The dynamics of such interactions are more complex and challenging than of the traditional power system. The fast-switching controls of IBRs have resulted in faster dynamics in the system which warrants the application of electromagnetic transient (EMT) simulation software for their study. The EMT (or even phasor domain) simulation of very large number of such devices in the bulk power system may make it impractical to model each IBR separately.

However, such granularity in simulation is not necessary on the bulk power system level as long as the relevant aggregate dynamic response of a group of IBRs such as wind generators and solar plants are captured properly at the feeder level. In this context, a fundamental question arises as to what linear and nonlinear features of IBR device models are significant in influencing the bulk power system response, and whether those features can be estimated using external measurements.

3.2 Proposed Solution

In this task, we study the influence of various parameters of the inverter-based resources on their response and their interactions with other components in the power system. Two test systems were developed in PSCAD in order to study the behavior of the IBRs and their interactions.

3.3 Developed Test Systems

The original two-area eleven-bus Kundur system [22] was scaled and modified to include some IBRs and some other distributed generations. Two test systems were developed and are discussed as follows.

3.3.1 Test System 1: Modified 2 Area Kundur System with GFM and GFL

Figure 15 shows the Test System 1 which was developed in PSCAD. The system has been made form the two-area eleven-bus Kundur system by replacing the synchronous generators in Bus 3 and Bus 4 by IBRs. A grid following inverter is connected to the Bus 3 of the power system with a small synchronous machine connected to the same bus. Similarly, a grid forming (GFM) inverter and a wind generator are connected to the Bus 4. The GFM and the GFL inverter models were obtained from [24].

This system can be used to study the effects of different parameters of GFM and GFL inverters, and the wind generator system on the dynamics and stability of the power system and also compare it with the original Kundur system.

Figure 16 shows how the power flowing through different generators change in the power system as the IBRs respond. It shows that the interactions between the machines and IBRs remain stable. This test system will be used in future studies for analyzing the impact of IBRs on the small-signal stability and transient stability properties of the system.

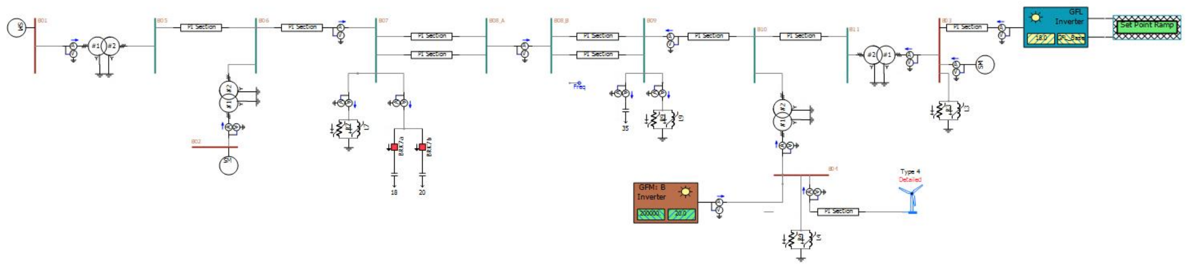

Figure 15: Test System 1

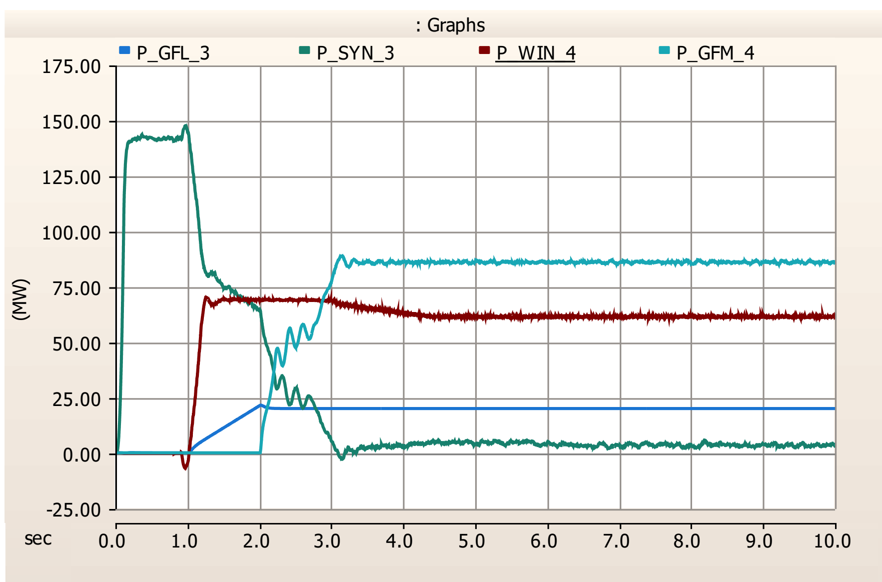

Figure 16: Redistribution of active power in Test System 1 as IBRs kick in

3.3.2 Test System 2: Modified 2 Area Kundur System with GFM and Microgrid

Figure 17 shows the PSCAD Test System 2. It has also been developed by modifying the two-area Kundur system. In this test system, the synchronous generator in Bus 3 has been replaced by a GFM and a synchronous machine of small capacity and the synchronous generator in the Bus 4 has been replaced by a wind farm. In addition to the wind farm, a microgrid consisting of PV generator, battery storage system, diesel generator and a type 3 wind generator is connected to the Bus 4 of the system.

This test system can be used to study the interaction among different kinds of IBRs and also between the IBRs and synchronous generators. The system can also be used to study the aggregated effect of distributed energy resources (DERs) on the bulk power system.

Figure 18 shows the power generated by different DERs present in the micro grid when it is connected to the bulk power system. It shows that the interactions between the machines and IBRs remain stable and that the responses are well-damped. This test system will be used in future studies for analyzing the impact of IBRs on the small-signal stability and transient stability properties of the system.

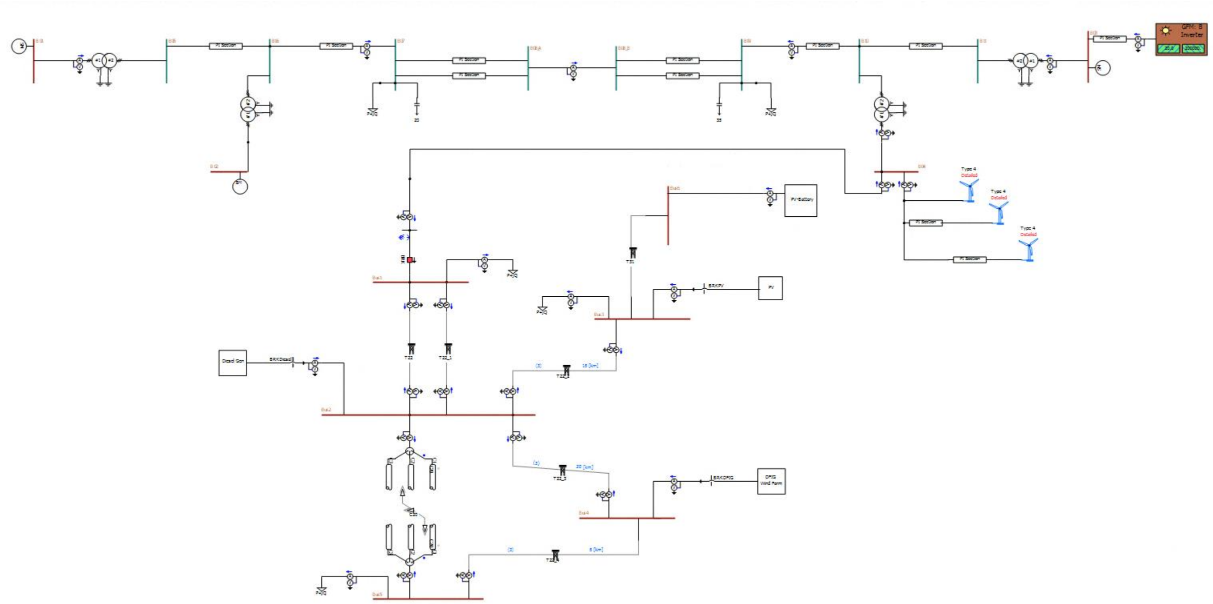

Figure 17: Test System 2

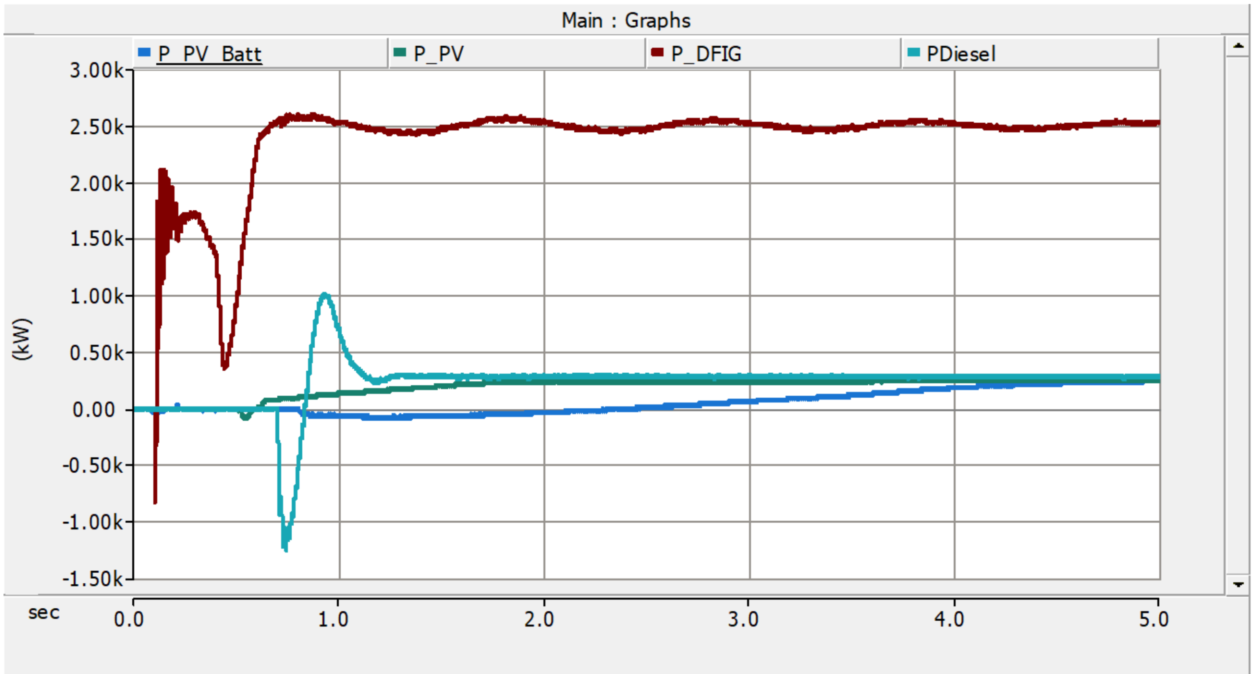

Figure 18: Power generation from DERs in Micro Grid

3.4 Discussion

The test systems developed in PSCAD as part of this task provide a platform for performing simulation studies which can provide insight into the parametric influence of the IBR models. The test system can also be used for studies which helps to improve the understanding of the aggregate behavior of IBRs at bulk power system level.

4. Task 3: Open-source toolbox for model validation

4.1 Introduction and Problem Statement

Power system simulation results are extensively used in the planning and operation of the power systems. The correctness of these simulation results is dependent on the accuracy of the parameters of the models of various components in the system. These components could be anything from synchronous machines and their controls to different kinds of inverter-based resources (IBRs). In many cases, the dynamic parameters of such models may not be available from the manufacturers, especially for IBRs because of their proprietary nature, or they may be inaccurate. It is thus necessary to estimate and periodically verify the parameters of such dynamic models to ensure reliable simulation results of power system models.

Two approaches are used for power plant model validation. The first approach uses staged tests in which the generators are taken offline and hence are time consuming and expensive. The second approach makes use of the disturbance recording and thus avoids the need to take generators offline [25]. This convenient approach has been enabled by availability of phasor measurement units (PMUs) at the terminals of the power plants and was proposed by PI's group in [7].

The measurement-based method of power plant model validation has now become an industry standard and has been a part of many commercial software. There are also some open-source model validation platforms like [26] but they still rely on some commercial transient simulation software like PSSE or GE PSLF to perform power system simulation in the backend. So, the users will still need access to the commercial software.

4.2 Proposed Solution

In this work, we develop an open-source model validation tool based on [7] using Dynawo [27] for the power system simulation. Dynawo is a hybrid C++/Modelica open-source suite of simulation tools for power systems which is developed by RTE France. The user interface for the model validation tool is developed in Python and the optimization operation is also done using free Python libraries.

4.3 Model Validation Framework

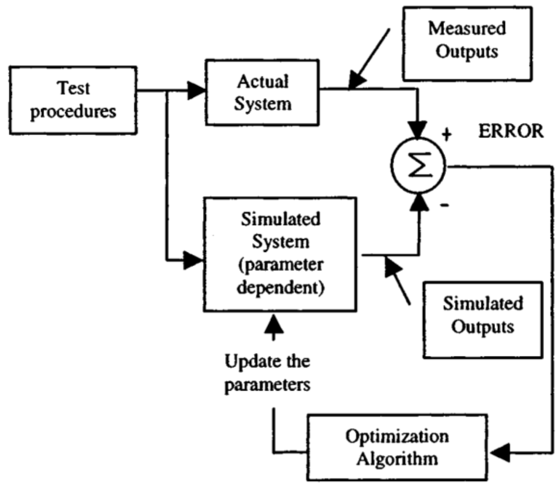

Figure 19: Model Validation Framework [7]

The basic framework of the model validation approach is shown in Figure 19. The components of the framework are discussed as follows:

Actual System is the power system component of interest whose dynamic parameters are to be validated. It could be a synchronous generator, inverter-based source or any other component.

Measured Outputs represent the PMU measurements at the terminal of the component of interest during an event (or disturbance) in the system or during any *test procedure*.

Simulated System represents the power system transient simulation environment which contains the dynamic model of the component to be validated, represented as connected to an infinite bus. Dynawo is used as the simulation engine.

Optimization Algorithm is used to minimize the error between *Measured Output* and *Simulated Output* by tuning dynamic parameters of the model. The tool uses a downhill-simplex based algorithm to perform optimization.

This approach is not model-specific and thus allows for convenient switching between a large variety of components and their models. This advantage comes from the application of optimization method which uses output of the simulation engine directly without requiring the information about the specific model structure.

4.4 Model Validation Tool Architecture

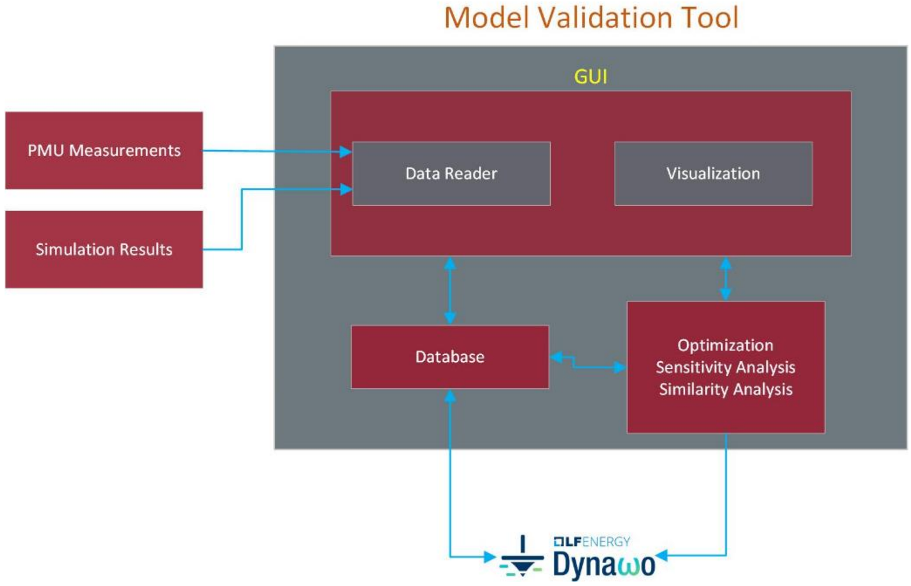

Figure 20: Model Validation Tool Architecture

The architecture of the developed open-source model validation tool is shown in Figure 20. The tool provides an interactive graphical user interface (GUI) which allows reading of required data, performing required operations for model validation and provides visualization of the results. The input data required for model validation operation are as follows:

Dynamic model information

The dynamic model of the component whose parameters are to be validated should be provided as a system with the component connected to an infinite bus. Dynawo requires the following files to represent the power system and to run the transient simulation.

i. Dyd File

   The dyd file contains the information of the dynamic models used in the simulation. It should contain the component whose model is to be validated and this model should be connected to an "InfiniteBusFromTable" model present in Dynawo library for playback of measured data.

ii. Par File

   The par file contains the parameters of the dynamic models of the components used in simulation and the solver configuration.

iii. Crv File

   The curve file contains the signals which are monitored during the simulation. It should contain at least the active and reactive power signals of the source as these signals are used for the optimization process.

iv. Jobs File

   The jobs file contains information about the simulation setting.

PMU Measurements
The PMU measurements from the terminal of the component of interest during an event (i.e., during a disturbance) or during a test procedure should be provided to the model validation tool. The data should contain the terminal voltage magnitude and phase angle, and the active and reactive power measurements. The voltage information is provided as input to the "InfiniteBusFromTable" model for playback and the active and reactive power data is used for the optimization process.

The tool uses SciPy [28] library in Python for running the optimization algorithm and minimizing the error between the measured data and the simulated data.

4.5 Additional Features in the Tool

4.5.1 Sensitivity Analysis

The model validation tool provides the feature of sensitivity analysis. Sensitivity analysis shows the sensitivity of the difference between simulation results and PMU measurement to change in each parameter.

$$\mathrm{S}(\mathrm{p}_0) = \mathrm{Err} - \mathrm{Err}_0 \tag{20}$$

Where,

$$\mathrm{Err}_0 = \mathrm{err}(\mathrm{Z}_{\mathrm{meas}}, \mathrm{Z}_{\mathrm{sim}}(\mathrm{p}_0)$$

$$\mathrm{Err} = \mathrm{err}(\mathrm{Z}_{\mathrm{meas}}, \mathrm{Z}_{\mathrm{sim}}(\mathrm{p}_0 + \alpha * \mathrm{p}_0)) \tag{21}$$

Z_{meas} represent the measured system response, $, Z_{sim}(p)$ represent the system response with parameter p, p_0 is the initial parameter and α is the perturbation in parameter as a fraction. $err(Z_{meas}, Z_{sim}(p))$ is the function which provides error between the measured and the simulated system response.

The sensitivity analysis provides a path to identify the erroneous parameters. Parameters can be discarded from the model validation process, if they are not sensitive enough to the particular event.

4.5.2 Similarity Metrics

The tool provides three similarity metrics which help to quantify the similarity of the measured waveforms with the simulated waveform. This also provides a check on the performance of the model validation process.

4.5.2.1 Correlation coefficient

The correlation coefficient is defined by equation (22). It provides a measure of linear relationship between the two signals i.e., the measured and the simulated signals. $\rho_{xy} = 0$ indicates no linear relationship between the signals while $|\rho_{xy}| = 1$ indicates perfect match between the signals in a linear manner.

$$\rho_{xy} = \frac{\mathrm{Cov}(x, y)}{\sigma_x \sigma_y} \tag{22}$$

4.5.2.2 Magnitude Similarity Measure

The magnitude similarity metric is proposed in [29] and is given by the average of $M_\alpha(f)$ over the frequency range of interest. $M_\alpha(f)$ is defined by equation (23).

$$M_\alpha(f) = 1 - tanh\,(\frac{ln(3)}{2} . \frac{|20\, log_{10}|H(f)||}{\alpha}) \tag{23}$$

Where,

$$|H(f)| = |\frac{Y(f)}{X(f)}| \tag{24}$$

Where H(f) is the fictitious system frequency response function which describes the linear relationship between X(f) and Y(f) and α is the reference value in dB scale such that $M_\alpha(f) = 0.5\ if\ |20\log_{10}|H(f)|| = \alpha$ dB. The magnitude similarity metric can have a maximum value of 1 which represents strong similarity between the signals.

4.5.2.3 Phase Similarity Measure

The phase similarity metric is also proposed in [29] and is given by the average of $S_\beta(f)$ over the frequency range of interest. $S_\beta(f)$ is defined by equation (25).

$$S_\beta(f) = 1 - tanh\,(\frac{1}{2\pi} . \frac{|arg(H(f))\,|}{\beta}) \tag{25}$$

Where, H(f) is as defined inequation 6 and β is a reference value such that $S_\beta(f) = 0.5$ if $\left|\frac{1}{2\pi}\arg(H(f))\right| = \beta$. The phase similarity metric also has value of 1 for the maximum similarity.

4.6 Case studies

This section presents two case studies demonstrating the application of the model validation tool. For both cases, the “measured” data are first generated using Dynawo and the parameters used for generating these data are considered as “true” parameters. Error is introduced in some of the model parameters resulting in difference in the simulated output. The developed model validation tool is
used to tune the parameters of the erroneous models.

4.6.1 Case 1: Model validation of a synchronous generator

In this case, the inertia time constant “H”, of a synchronous generator represented by “GeneratorSynchronousFourWindingsTGovSexsPSS2A” model in Dynawo is tuned using the model validation tool. A single machine infinite bus system is constructed in Dynawo with “InfiniteBusFromTable” model to represent the infinite bus and playback the terminal voltage obtained from the “measured” data.

Table 2 shows that the tool was able to tune the parameter with reasonable accuracy. The match of simulated response to the measured data can also be seen in the plot are of Figure 21. Figure 21 also shows the similarity metrics all of which indicate better match of the tuned model with the measured data.

Table 2: Comparison of Generator H before and after tuning

Parameter	**Original**	**Tuned**	**True**
Generator_H	3	3.996	4

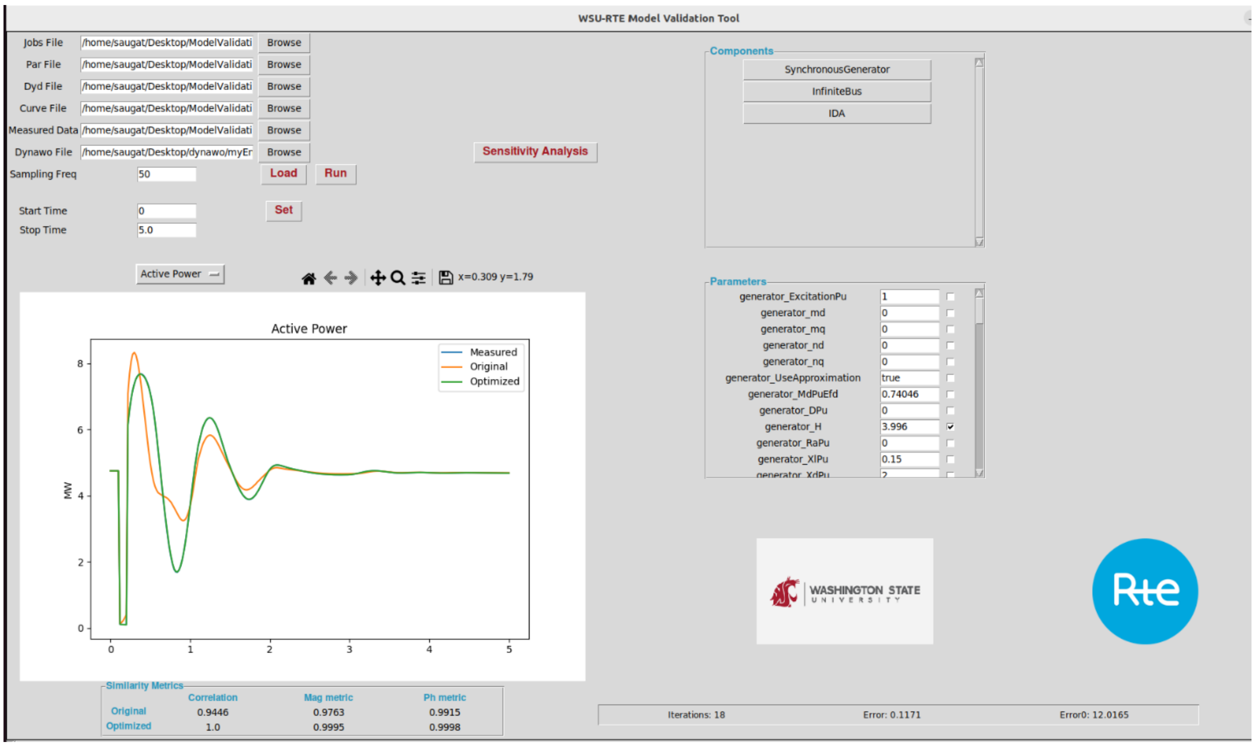

Figure 21: Tuning of "H" of synchronous generator model

4.6.2 Case 2: Model validation of a grid forming inverter

This case considers the model validation of a grid forming inverter represented by “GridFormingConverterDroopControl” model in Dynawo. The Dynawo system used for transient simulation consists of the grid forming model connected to an infinite bus. The infinite bus is represented by the “InfiniteBusFromTable” model to play back the “measured” terminal voltage.

In this case, errors were introduced in two parameters viz inductance of the converter filter and the proportional gain of the current loop of the converter.

Table 3 compares the original erroneous parameters with the tuned parameters and shows their convergence close to the "true" values. The better match of the tuned response with the "measured" data is also shown by all of the three similarity metrics.

Table 3: Comparison of GFM parameters before and after tuning

Parameter	Original	Tuned	True
Converter_Lfilter	0.1	0.151	0.15
Control_Kpc	0.5	0.799	0.78

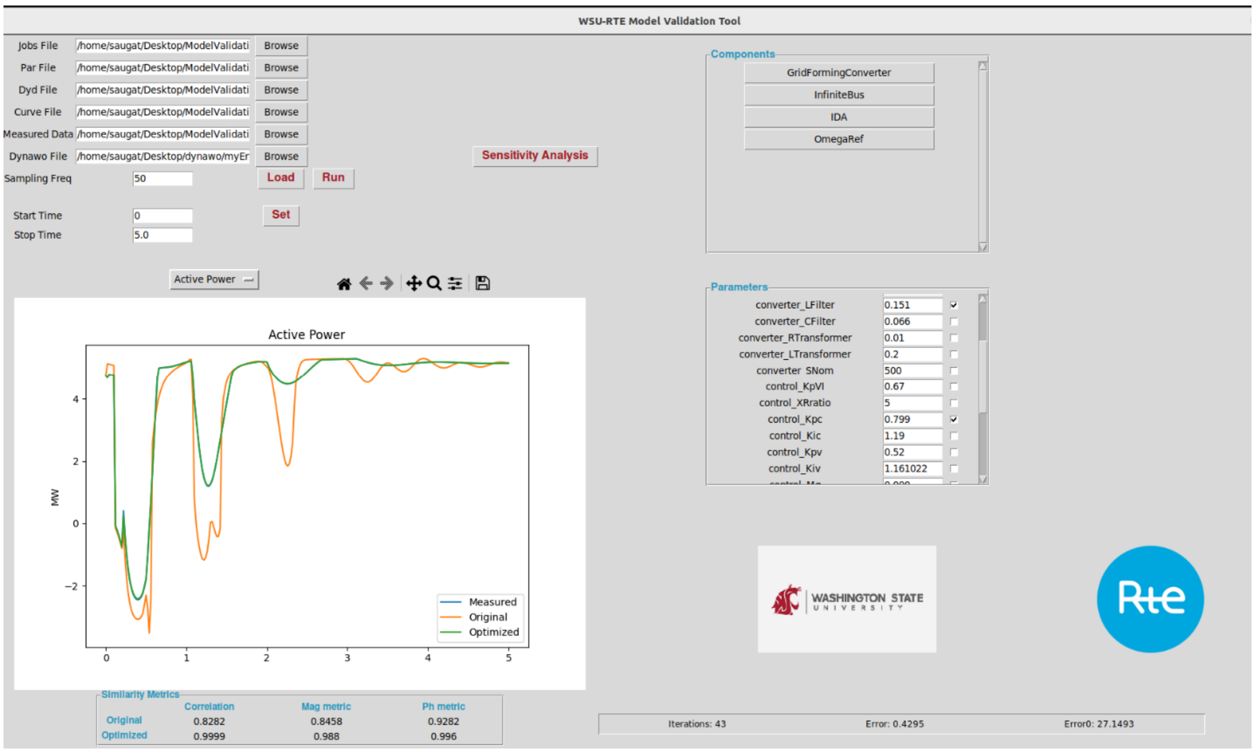

Figure 22: Tuning of parameters of GFM

4.7 Discussion

The developed model validation toolbox demonstrated its usefulness by properly tuning the dynamic model parameters of synchronous generator as well as those of grid forming inverter. The model-independent feature of the framework will make it easily adaptable as new IBR models are introduced and added to Dynawo library. Tests using real system data and further studies with different optimization algorithms are needed to evaluate and improve the model validation toolbox's performance.

References

[1] J. Pierre, D. Trudnowski, C. Canizares, L. Dosiek, H. Ghasemi, M. Gibbard, E. Johansson, G. Ledwich, R. Martin, E. Martinez, L. Vanfretti, D. Vowels, R. Wise and N. Zhou, "Identification of Electromechanical Modes in Power Systems", IEEE Task Force Report, Special Publication TP462 2012.

[2] V. Venkatasubramanian, John "JP" Skeath and Ryan Quint, "Analysis of inter-area oscillations in North American interconnections", NASPI Working group meeting, Philadelphia, Oct. 2018, https://www.naspi.org/sites/default/files/2018-11/nerc_mani_oscillation_analysis_20181024.pdf

[3] S.A.N. Sarmadi, and V. Venkatasubramanian, "Inter-area resonance in Power Systems from Forced Oscillations", IEEE Trans. Power Systems, Jan. 2016, pp. 378-386.

[4] M. Kezunovic,S. Meliopolous, V. Venkatasubramanian, and V. Vittal, "Application of Time-synchronized Measurements in Power System Transmission Networks", Springer Verlag, 2014.

[5] North American Electric Reliability Corporation, "1200 MW fault induced solar photovoltaic resource interruption disturbance report, Southern California 8/16/2016 event", June 2017.

[6] North American Electric Reliability Corporation, "April and May 2018 Fault Induced Solar Photovoltaic Resource Interruption Disturbances Report", January 2019.

[7] M. Shen, V. Venkatasubramanian, D. Sobajic and N.Abi-Samrah, "A new framework for estimation of generator dynamic parameters", IEEE Trans. Power Systems, Vol. 15, No. 2, May 2000, pp. 756-763.

[8] V. Venkatasubramanian, and M. Shen. "Decentralized estimation of power system dynamic models", Proceedings of the 39th IEEE Conference on Decision and Control, 2000, pp. 2035-2039.
[9] M. Hatami et al., "Online Transfer Function Estimation and Control Design Using Ambient Synchrophasor Measurements," in IEEE Transactions on Power Systems, vol. 38, no. 1, pp. 14-30, Jan. 2023, doi: 10.1109/TPWRS.2022.3157251.

[10] N. Zhou, J. W. Pierre and D. Trudnowski, "A Bootstrap Method for Statistical Power System Mode Estimation and Probing Signal Selection," 2006 IEEE PES Power Systems Conference and Exposition, Atlanta, GA, USA, 2006, pp. 172-178, doi: 10.1109/PSCE.2006.296293

[11] J. W. Pierre, N. Zhou, F. K. Tuffner, J. F. Hauer, D. J. Trudnowski and W. A. Mittelstadt, "Probing Signal Design for Power System Identification," in IEEE Transactions on Power Systems, vol. 25, no. 2, pp. 835-843, May 2010, doi: 10.1109/TPWRS.2009.2033801.

[12] S. Boersma et al., "Enhanced Power System Damping Estimation via Optimal Probing Signal Design," 2020 22nd European Conference on Power Electronics and Applications (EPE'20 ECCE Europe), Lyon, France, 2020, pp. 1-10, doi: 10.23919/EPE20ECCEEurope43536.2020.9215892.

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[17] Van Overschee, P., De Moor, B. (1996), Subspace Identification for Linear Systems. Springer, Boston, MA.

[18] P. G. Estevez, P. Marchi, C. Galarza and M. Elizondo, "Non-Stationary Power System Forced Oscillation Analysis Using Synchrosqueezing Transform," in IEEE Transactions on Power Systems, vol. 36, no. 2, pp. 1583-1593, March 2021, doi: 10.1109/TPWRS.2020.3015145.

[19] P. G. Estevez, P. Marchi, F. Messina and C. Galarza, "Forced Oscillation Identification and Filtering from Multi-Channel Time-Frequency Representation," in IEEE Transactions on Power Systems, vol. 38, no. 2, pp. 1257-1269, March 2023, doi: 10.1109/TPWRS.2022.3172850.

[20] https://www.mathworks.com/help/ident/ref/oe.html

[21] By J JMesserly and those stated in source. - Blank map of Europe.svg by Maix, which is based on Europe countries.svg by Tintazul, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=5553728

[22] P. Kundur, Power System Stability and Control, New York, NY, USA:McGrawHill, 1994

[23] https://www.dsatools.com/

[24] R. W. Kenyon, A. Sajadi, A. Hoke and B.-M. Hodge, "Open Source PSCAD Grid-Following and Grid-Forming Inverters and a Benchmark for Zero-Intertia Power System Simulations," in Kansas Power and Energy Conference, 2021.

[25] A. Silverstein, E. Andersen, F. Tuffner, D. Dosterev and T. King, "Model Validation using phasor measurement unit data: NASPI technical report," 2015.

[26] Y. Li, R. Diao, R. Huang, P. Etingov, X. Li, Z. Huang, S. Wang, J. Sanchez-Gasca, B. Thomas, M. Parashar, G. Pai, S. Kincic and A. Ning, "An innovative software tool suite for power plant model validation and parameter calibration using PMU measurements," in IEEE Power Energy Society General Meeting, 2017.

[27] A. Guironnet, M. Saugier, S. Petitrenaud, F. Xavier and P. Panciatici, "Towards an Open-Source Solution using Modelica for Time-Domain Simulation of Power Systems," in 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2018.

[28] "SciPy," [Online]. Available: https://docs.scipy.org/doc/scipy/tutorial/general.html.

[29] K. Shin, "An alternative approach to measure similarity between two deterministic signals," Journal of Sound and Vibration, 2016.